PATTERN PROCESSING AND RECOGNITION IN HUMAN BRAIN

A DISSERTATION

submitted in partial fulfilment of the requirements for the award of the degree

of

MASTER OF ENGINEERING

in

ELECTRICAL ENGINEERING

(Measurement & Instrumentation)

By

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CERTIFICATE

This is to certify that dissertation entitled "[redacted] PATTERN PROCESSING AND RECOGNITION IN HUMAN BRAIN" which is being submitted by Shri Ved Pal in partial fulfilment for the award of the degree of Master of Engineering in Electrical Engineering (Measurement and Instrumentation) of University of Roorkee, Roorkee is a record of students' own work carried out under my guidance. The matter embodied in this dissertation has not been submitted for the award of any degree or diploma.

This is further to certify that he has worked for a period of 8 months (eight months) from January 1980 to Sept. 1980 for preparing this dissertation at this University.

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CHAPTER - 1

INTRODUCTION

Human brain is so complex a system that it is really very difficult to understand it. Only a superbrain, which has more capabilities than human brain, can have exact insight into it. Studies upto now could have their spread only in the limited aspects in the interpretation of the functioning of human brain. The available literature, relating to the pattern processing and recognition in human brain, is more or less, based on hypothetical analysis as, specially in recognition of patterns, very small, almost negligible, data is available from physiological sources. Different researchers have interpreted the process of recognition in human brain in different manners, mathematically or theoretically. No one theory is existing which is capableof interpreting the processing and recognition of simple as wellas complex patterns, incorporating the fast speed of recognition of patterns under real world conditions i.e. enlarged, distorted, rotated, in clutter etc. Massive research work is required in future for explaining the recognition process of three-dimensional patterns[29] or patterns in motion and also for discriminating thousands of colours very accurately.

The work in this dissertation has been organized in eight different chapters. Chapter I introduces about the importance of the problem and also gives organization of the dissertation. The anatomy and physiology of brain has been discussed in chapter 2. Chapter 3 deals about the details of human visual system alongwith theory of visual perception. The perception of colours by visual system is discussed in 4th Chapter. Chapter 5 deals with extraction of features and recognition of simple patterns. The recognition of complex patterns through pattern adaptation and probabilistic approach is given in Chapter 6. The patterns under real world conditions are considered in Chapter 7. The general conclusions and discussion about the work are given in last chapter.

CHAPTER - 2

ANATOMY AND PHYSIOLOGY OF HUMAN BRAIN [1], [2], [3]

Brain is the most complex structure of human organism. There are numerous challenges even upto now in understanding the anatomy and physiology of human brain. Brain performs the functions of storage of patterns, their processing and Recognition. The nervous system is a so complicated subject and we know so little about it, that it is necessary to draw heavily on analogous experience in other disciplines. These other areas of knowledge supply models, some reasonably accurate, some with a semblance of reality and some almost completely conjectural. Performance of Mammalian brain can be thought of containing four categories:

1) It extracts the features that are meaningful from the mass of incoming sensory information.

2) It compares incoming sensory and thought patterns against previously stored patterns indicating, by electrical discharges that recognition has occured when patterns are similar.

3) It stores as memory some reasonable fascimile of recent happenings as well as important features of past patterns

4) It excites various muscles, glands or "inclusion bodies" in accordance with a very complicated interplay of patterns past and present.

A pattern is the synthesis of individual elements such as light and dark dots pulsations of the air, the molecular constituents of food, the pressure stimuli on nerve fiber endings or frequencies of pulse trains etc. Patterns may be from very simple to very very complex types.

Anatomy

Human brain broadly consists of three sections - (1) Forebrain (2) Midbrain (3) Hind brain.

The posterior part of the brain becomes spinal cord. Forebrain may be divided into two parts, the anterior part telencephalon and posterior part Diencephalon. The midbrain or mesencephalon becomes a part of brain stem. The hindbrain is also divided into two parts - an anterior part, the metencephalon and the posterior part, myencephalon Fig. (2.1).

Primary divisions	Secondary divisions	Structures
Forebrain	Telencephalon	olfactory bulbs cerebral cortex Lateral Verticles
	Diencephalon	Epithalamess, pineal body, Thalamus Hypothalarous Stalk of pituitary gland Mammil-ary bodies Greater part of third verticle
Midbrain	Mesen-cephalon	Colliculi Cerebral Aqueduct Cerebral Peduncles Red nucleus
Hindbrain	Metencephalon	Cerebellum Pons Fourth ventriale
	Myencephalon	Me Medulla Pyramidal Tracts

The brain and spiral cord are protected by meningeal membranes which are three in number and consist a tough, fibrous outer layer, the duramatter, a delicate intermediate membrane, the arachnoid and the inner vascular laye , the pia matter.

Duramatter

Within the cranium it is composed of two layers which adhere very closely except that they are separated by venous sinuses.outer layer becomes fused with cranial bones. The inner layer of the dura lines the vertebral canal extending down over the spinal cord.

Arachnoid

The delicate arachnoid membrane lines the dura matter and extends down over the cord. There is a sub arachnoid space at each depression between the convolutions of the brain. The subarachnoid spaces are filled with cerebrospinal fluid which protects the brain and cord from mechanical injuries. It is a lymphlike fluid with a few white cells in it. Disease which attack CNS alter its composition or amount.

Pia Matter

It contains a dense network of blood vessels. It is applied very closely to the brain surface and spinal cord.

Neuroglia

There are three principal types of neuroglial cells, namely astrocytes, oligodondrocytes, and microgliocytes. Astrocytes and oligodondrocytes arise from neural tube cells and therefore are ectodermal in origin but microligocytes arise from mesoderm.

Astrocytes

Astrocytes are associated with the neurons and blood vessels of the CNS. Under the piamatter, they form a membrane of neuroglial cells around blood vessels. These are of two types - protoplasmic and fibrous. The protoplasmic astrocytes have larger cytoplasmic processes than the fibrous astrocytes, are more irregularly branched and are found generally in gray matter. Fibrous astrocytes with long thin processes are found for the most part in white matter.

Astrocytic glial cells have been shown to exhibit an action potential with a duration many times longer than nerve cells. When stimulated electrically, they are capable of slow contraction lasting several minutes. Neuroglial cells are commonly involved in infection and in primary tumors of the CNS.

Oligodendrocytes

These are found abundantly in CNS and are smaller than astrocytes. These are commonly clustered around the large cell bodies of the neurons where they are called satellite cells. They are found in rows along nerve fibers in the white matter of the C.N.S.

Microgliocytes

They have very small irregularly shaped cell bodies with two or more processes. The processes are finely branched with short spin like projections.

Ventricles

The ventricles or cavities of the brain communicate with each other and are continuous with the central canal of spinal cord. They are lined by a membrane called Ependyma. The ventricles, the central canal of the cord and the subarachnoid. Spaces are filled with cerebrospinal fluid. Lateral ventricles of cerebral hemispheres which are largest cavities communicate with the third ventricle, of diencephalon by way of an interventicular formen. The third ventricle connects with the fourth through a cerebral aqueduct which traverses the midbrain. The fourth ventricle is continuous with the central canal of the spinal cord.

Cerebrospinal fluid filters out through the membrane and circulates slowly through the ventricles. The fluid posteriorly through intervencircular foramina into the third ventricle, then through the cerebral aqueduct and into the fourth ventricle The fourth ventricle has three openings in its roof that permit the fluid to flow into the subarachnoid spaces around the cerebellum and medulla. The fluid then flows slowly down through the subarachnoid space, covering the spinal cord and also enters the central canal of the cord. Fig. (2.2).

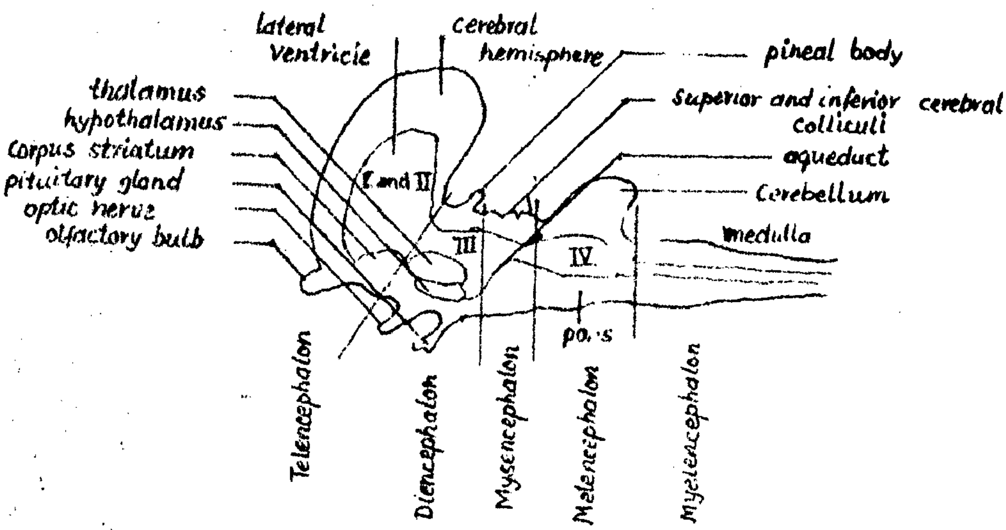


FIG-2.1 Principal divisions of human brain

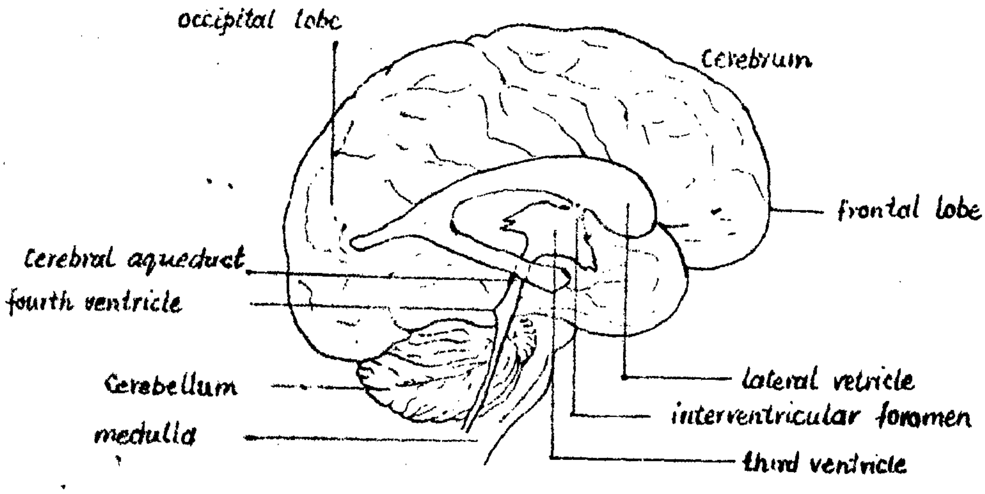


FIG-2.2 Ventricals of the brain in lateral view

<u>Cerebrum</u>

Nervous activity with the cerebral cortex results in conscious thought. It provides for the higher intelligence of man in terms of reasoning ability, good judgement memory and will power. It provides interpretations of special senses of sight, hearing, taste smell and touch. Cerebral cortex helps in initiating a voluntary muscular response and directing our own body movements - certain emotions - feelings of charity, appreciation of beauty, a desire to do right are functions of cerebrum, more primitive emotions such as rage may be in part the expension of a lower part of the brain, the hypothalamus. Many acts that are ordinarily reflex may be dominated or controlled by the cerebrum as when we cough voluntarily or hold the breath for a time.

The two hemispheres are separated medially by the great longitudinal fissure. Fissures are deep depressions on the brain surface. The numerous lesser depressions on the brain surface. The numerous lesser depressions are called sulci and separate the elevations which are convolutions. The brain is covered by the covering or cortex of gray matter. It is composed of millions of unmedullated nerve-cell bodies and fibers.

Inside of the brain which looks white, is made largely of medullated nerve fibers. These fibers may connect the cortex with the spinal cord or they may extend between different parts of the brain itself. A large nerve tract connecting the right and lect lobes of cerebrum is called corpus collosum Fig. (2.3).

LOBES

Fissures divide the cerebrum into anatomical areas called lobes. They are the frontal, parietal, temporal and occipital lobes. The frontal lobe lies below the frontal bone and is seporated from the parietal lobe by central sulcus. Parietal lobe is therefore posterior to the frontal lobe. The temporal lobe lies on the side of the brain below the lateral cerebral fissure (the sylvian fissure).

Cerebral Localization

It is not possible to localize some of the function of the corelbrum. We can not pin point the areas that governs will power or any one part of the brain that is the seat of memory. Even then certain functions are performed by some well defined areas. The motor area lies just anterior to the central sulcus. To cause contractions of voluntary muscles, voluntary impulses arise in this area. The area governing the thigh lies at the upper part of the motor area while the muscles of the face and tongue are controlled from lower part. It is interesting that a greater area proportionately is devoted to governing the muscles of the hand and tongue than to the muscles of the trunk. The motor speech area is concerned with the coordination of all the muscles of the face, tongue and throat necessary for speaking. The motor area of the right cerebral hemisphere governs the movement of muscles of the left side of the body and vice versa. The reason for this is that the nerve tracts from the motor area across over either at the base of medulla or at various levels in the spinal cord.

A knowledge of the location and function of the motor area has been of great value in the diagonosis of many types of brain diseases or injuries. Cerebral hemorrhage often called 'stroke' or Apoplexy, while usually occurring deep within the brain in the internal capsule, has the same effect as a surface injury.

There lies a sensory area, posterior to central sulcus, for the interpretation of sensation as touch, pain, temperature, pressure and muscle sense. This is called cutaneous sensory area. The right sensory area interprets sensations received from the left side of the body and vice versa.

Visual interpreting area is located at the back of the brain in the occipital lobes. Nervous impulses arising in the retina are conveyed to the interpreting area by nerve tracts. This sensory area enables one to interpret and understand what he sees. Loss of the ability to understand written words or symbols, is recognized as a form of aphasia in which individual is unable to read his own language. His eyes may be able to see and follow the printed words but the symbols mean nothing to him.

The auditory areas ~~areas~~ are concerned with the interpretation of the sense of hearing and are located in temporal lobes. Each area receives impulses from both ears. Injury to these areas causes failure of the memory ~~of~~ or the meaning of words. It is a type of sensory aphasia. Although hearing may remain unimparied, the words or their meaning is not recognized

Interpreting areas for the sense of taste and smell have not been definitely located. A cortical area associated with the sense of taste is located near sylvian fissure and at the base of central sulcus where sensory impulses from the face are interpreted. Two olfactory bulbs are located ventrally below the frontal lobes of cerebrum, where important synaptic connections are made between the fibres of the olfactory nerve and the interpreting area of the brain. The interpreting area for the sense of smell is thought to be along the olfactory tracts which extend in ward from the olfactory bulbs.

If the upper part of the motor area is stimulated, musculr movements occur in the lower extremity on the opposite side of the body. But if one stimulates the middle or lower part of the area, with adequate stimuli lower extremity movements also occur. It is found that in the area for trunk movement the muscles in the trunk have lowest threshold i.e. are most easily stimulated ~~bet~~ but evidently the various regions are not specific.

It is generally agreed that the cortex is composed of five to seven layers of neurons. Electrical stimulation of the surface area can produce very different motor effects from those producedby normal nerve stimuli.

Experiments showthat probably all areas ofthe cortex are actually sensorimotor i.e. they are not exclusively sensory or exclusively motor. The region directly anterior to central sulcus is predominantly motor whereas the region posterior to central sulcus is predominantly sensory or afferent. Motor fibres in localized sensory areas produce motor response in muscles associated with the activity of the sense organ involved.

The diencephalon is the posterior part of the forebrain. The lines of demarcation are not distinct, since many structures lie partly in teloncephalon and partly in diencephalon. Thus choroid plexus of this region is continuous with that of teleneephalon, since greater part of the third ventricle is the cavity of diencephalon a part of it is the cavity of Teloncephalon. The thalamus region may be divided into an upper portion or epithalamus, an intermediate portion, the thalamus proper, and a lower portion, the hypothalamus. From the Epithalamus there arises a growth called pineal body. It is considered as endo-crine gland, although its function is not well understood.

The thalamus is the largest of a number of areas of gray matter deep within the brain called Basal Ganglia. It is important relay center for both motor and sensory impulses, and has extensive cortical connections.

Hypothalamus is composed of structure located in the basal portion of dieneephalon. They include the mammillary bodies and several other nuclei. There are also such structures as the optic chiasma, the infundibulum and pituitary body. Mammillary bodies consist of two rounded eminences of gray matter. They are believed to be concerned with emotional as well as certain visceral effects. Optic chiasma is formed by optic nerve. Some of these fibres cross to the opposite side and some do not. The stalk of pituitary body, the infundibulum arises as a downgrowth from the floor of diencephalon. Pituitary body is a gland of internal secretion. It is composed of two lobes. The posterior lobe arises as nervous tissue with the infundibulum, but the anterior lobe has a different embryological origin.

In hypothalamus heat regulatory centre and the centre of water metabolism are located. It is a regulatory centre for both the sympathetic and parasympathetic divisions of autonomic nervous system. Functionally the hypothalamus is closely associated with various endocrine activities of the pituitary gland.

Interpretive Function of Cerebral Cortex

Human brain consists of almost 10 billion neurous and apparently they are able to accept, reject and interpret the information supplied to them by sensory neurons. Much of the visual perception is organized by neurous of retina before passing along to the visual cortex. Researchers are trying to explain how visual cortex analyzes retinal images by studying responses of individual cells. There are two types of areas - one in which small circular pattern of light evoked a maximum response by a small group of receptors in the retina called 'on' areas and the other where as small spot of light suppressed firing until light was turned off, called 'off' areas. Thus there are centre 'on' with rest area 'off' type and centre off with rest area 'on' type field . These 'on' and 'off' fields, as found by Hubel and Wiesel are represented by straight lines not by circles. 'On' and 'off' areas are separated by linear boundaries. Orientation of these linear arrangements varied from vertical to horizontal. It appears then that visual cortex is capable of rearranging the incoming impulses to emphasize lines and contours.

Memory Processes

Memory is the ability to recall events or informations about previous experiences that may have happened only a few minutes ago or that may have occurred many years ago. There seems to be a short term type memory and a long term memory of facts and events which may last for the life time of the individual.

Theory of facilitation attempts to explain memory on the basis that passage of an impulse over a set of neurons and synapses may make it easier in some way for similar impulses to follow the same path. Eventually, a certain pathway would become facilitated and easily recalled. This hypothesis explains the process of repeating a list of facts or learning the words of a foreign language by repetition. Facilitation is also given as an explanation of habit formation. The mechanism of memory, however, is still largely unknown. If it can be localized, it is probably in the cortex, perhaps close to the sensory area that pertains to it.

With very mild electrical stimulation in the temporal area, patients sometimes recall events that occurred in the past quite vividly and in greater detail. The memory record may not be in the interpretive area itself but in some deeper area related to it.

Many investigators searched key of memory in RNA and protein metabolism. A molecular theory of memory is an attractive hypothesis but very difficult to establish on an experimental basis.

With age loss of brain cells takes place, thereby, the aged person becomes forgetful for recent events but may recall past events well. Other factor for it may be reduced supply of blood to the brain or a reduction in the oxygenation of brain cells.

Brain stem includes midbrain, pons and medulla. Great nerve tracts connecting the spinal cord with higher synaptic levels in cerebrum pass through brain stem.

Midbrain is the upper portion of brain stem. In human beings it is covered by cerebrum and loses most of its optic tract connections. The greater part of the midbrain consists of nerve tracts that carry impulses between cerebrum and cerebellum, medulla and spinal cord. The anterior part is composed largely of two great nerve tracts the cerebral peduncles. The cerebral aqueduct extends from third ventride to fourth and traverses the midbrain. Between the aquoduct and cerebral peduncles lie the red nuclei, two masses of gray matter connected by nerve tracts with the cortex of the cerebrum, the thalamus, the cerebellum and the spinal cord. Red nuclei are concerned with muscle tone and skilled movements. The nuclei of the occulomotor and trochlear cranial nerves are also located in the midbrain. Posterior to the cerebral aqueduct is the area called tectum, with four structures called superior and inferior colliculi. Inferior colliculi is auditory in function, so considered auditory reflex centre in mammals.

CEREBELLUM

Two cerebellar lobes are located below the occipital lobes of thecerebrum. Area between the two is vermis. The cerebellum has a cortex of gray matter but different from cerebrum in many aspects. It is not convoluted in the same manner but appears as a series of layers. Within the cortex are large cells of Purkinje, with their remarkable branching dendrites. These efferent cells are found only in the cortex of the cerebellum. Inferior of the cerebellum is largely composed of white matter, althogh the gray matter of the cortex descends deeply into the white matter and elaborates into an inverted treelike pattern of branching (called arbor vitae). There are some muclei of gray matter within the cerebellum. Great nerve tracts, cerebellor peduncles, connect the cerebellum with the cerebrum, the pons and the medulla.

The pons consist of horizontal nerve tracts that serve to connect the two hemispheres of the cerebellum anteriorly and vertical tracts that connect the cerebrum with the medulla

The cerebellum has been called 'the Secretary' to the cerebrum. It does not initiate motor responses but functions to coordinate muscular movements so that the action will be smooth and efficient instead of jerky and uncoordinated. It is also concerned with the equilibrium of the body and is connected by nerve fibres with the semi-circular canals of the inner ear which are concerned with equilibrium. The cerebellum is able to direct the muscular coordination that tends to keep body balanced in various positions. It is also concerned with coordinating impulses received from the sense of hearing, sense of sight and tactile sense.

Cerebellum helps to maintain the tone of muscles. Mammals with cerebellum removed exhibit a peculiar uncoordinated walking ~~gout~~ gait. All functions are below level of conscious activity, sensory impulses received do not produce sensation.

In cerebellum, localization of function ~~as~~ is not as definite as in cerebrum. Each cerebellar hemisphere controls the coordination of movement of appendages on the same side of the body, whereas vermis controls the coordination of the trunk musculature. An injury to the right hemisphere may affect the right side of the body as well as appendages of that side. Auditory and visual stimuli are received in an area located at about the middle of the dorsal aspect. Equilibruim seems to be controlled from two centres, one in an anterior and other in the posterior cortical area.visual and auditory areas overlap. This association seems relevent to behaviour in that we draw the hand away from an unexpected touch and we look in the direction of unexpected sound.

THE MEDULLA

It provides base to the brain stem, the myelencephalon. It is continuous with the spinal cord but does not have same structure, while nerve tracts are continuous some are larger and better defined in medulla. Some fibres cross to opposite side. The continuous gray matter of the cord is broken up into groups of nuclei in the medulla. These include nuclei of IXth, Xth, XIth and XIIth cranial nerves. The central canal of the cord is continuous anteriorly through medulla. Where it opens into the lower part of the fourth ventricle. Medulla contains vital reflex centres as, cardiac inhibitory centre, which by way of vagus nerve acts in slowing heart rate, the vasoconstrictor centre, responsible for the constriction of peripheral blood vessels and the consequent rise of arterial pressure; a respiratory centre which provides nervous stimulus for regular respiratory movements. The medulla also controls a number of common reflex activities such as laughing, coughing and sneezing and many of the activities of digestivetract.

CRANIAL NERVES

These are 12 pairs of nerves arising from brain within the cranial cavity Fig. (2.4). These are numbered from I to XII and are having different names. These are like spinal nerves but are highly specialized.

I-Olfactory Nerve: arises from sensory receptors located in the upper part of mucous membrane that lines nasal cavity. The nerve is purely sensory and is concerned with carrying nerve impulses that give rise to the sense of smell. Individual fibres grow inward in this nerve.

II-Optic Nerve is a sensory nerve concerned with the sense of sight. It arises from the ganglion cells located in the retina

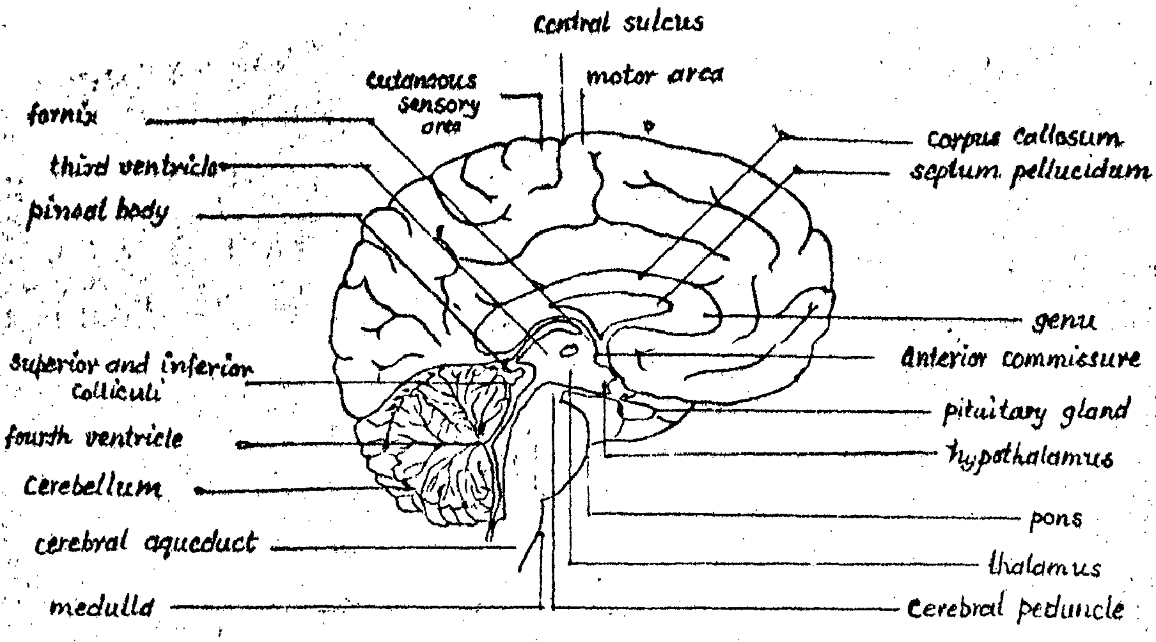


FIG-2.3 Saggittal section through the brain

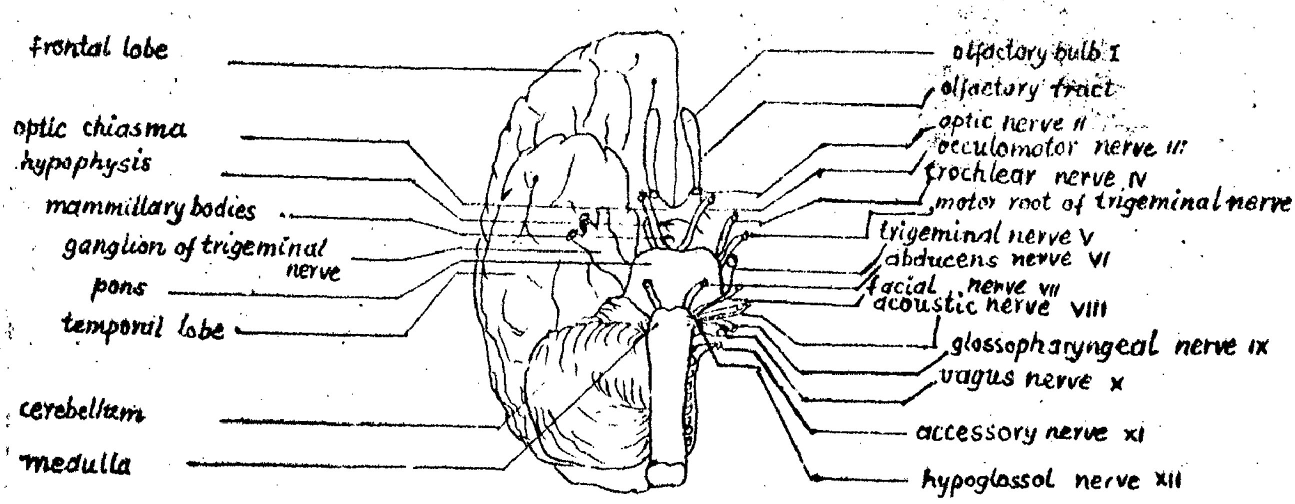


FIG-2.4 Ventral view of the brain, showing
bases of cranial nerves

of the eye and its fibres from the optic tract which leads back to the lateral gemiculate body of the thalamus. From there sensory impulses are conveyed by secondary neurons to the visual interpreting area in the occipital lobe of the cerebrum. The crossing of some of the fibres of the optic nerves probably results in better coordination of responses between eye and brain.

III-Occulomotor; IV-Trochlear, and VI-the Abducent nerves are motor nerves to the muscles that move the eyeball. The III and IV nerves arise from nuclei of gray matter located beneath the cerebral aqueduct in the midbrain. The trochlear nerve nucleus is posterior to the nucleus of occulomotor nerve. The nucleus of abducent nerve is in the lower part of the pons. Occulomoto nerve also carries fibers of parasympathetic system to the circular muscle of iris and to the ciliary muscle of the eye.

(V) The trigeminal is a mixed nerve with both sensory and motor nuclei. There are three large branches of trigeminal nerve - ophthalmic, maxillary and mandibular.

Opthalmic branch is a sensory branch and carries impulses originating in the surface of the eye, in the lacrimal gland and from the nose and forehead.

Maxillary branch is also a sensory branch and has a broad distribution of its nerves. Among the structures supplied are teeth and gums of upper jaw the upper lip and cheek.

Mandibular branch is a mixed nerve. It has many small branches, some of these nerves supply the teeth and gums of lower jaw, the chin, the lower lip and the tongue. It is motor to the muscles concerned with mastication.

(VII) The facial nerve is a mixed nerve. Its motor nucleus lies in the lower part of the pons and fibres are supplied to the muscles of face and forehead. The sensory branch is very small. Its fibers arise from the geniculate ganglion located in the temporal bone and are distributed to the anterior two thirds of the tongue. They are concerned with the sense of Taste. The motor branch also carries the fibers of parasympathetic system to the sublingual and submaxillary salivary glands. Parasympathetic fibers stimulate vasodilation and secretion in these glands fibers concerned with taste sensation and parasympathetic fibers pass through the tympanic cavity in chorda tympani branch.

(VIII) Vestibulocochlear Nerve (acoustic) is a sensory nerve concerned with the sense of hearing and with equilibrium. It is composed of two nerves of different origin and function. The cochlear nerve carries auditory impulses. Its ganglion lies in the cochlea. From receptors in the spiral organ of the corti, the auditory impulse is conveyed inward to the medulla. It crosses over to the opposite side and passes upward through the pons and midbrain over a series of neurons to the auditory interpreting area in the temporal lobe of the cerebrum.

The vestibular nerve arises in the vestibular ganglion of the portion of the ear associated with the semicircular canals. It enters the medulla but has important connections with the cerebellum. It is concerned with maintaining equilibrium.

(IX) The Glossopharyngeal nerve arises from the medulla and supplies the tongue and pharynx. It is a mixed nerve; the motor fibers are distributed to the muscles of the pharynx while sensory fibers are supplied to the tonsils, mucous membranes, of the pharynx and the posterior part of the tongue. Stimuli resulting in the sense of taste originate from receptors located in the large papillae at the back of the tongue. Secretory and vasodilator fibers are distributed to the paroted salivary gland.

(X) The Vagus nerve is the longest cranial nerve. Its pathway lies from the medulla, through the neck and thorax to the abdomen. It is a mixed nerve - sensory branches convey impulses from the mucous membranes lining the respiratory and digestive tracts. Voluntary motor fibers are distributed to certain muscles of the pharynx and larynx. The right and left vagus nerves send branches to the cardiac and pulmonary plexuses. Above the stomach, they unite to form esophageal plexus. Branches supplying the abdominal viscera arise below the esophageal plexus and contain involuntary fibers from both vagus nerves. Vagus nerve carries inhibitory fibers to the heart and secretory fibers to the gastric glands and pancreas as well as vasodilator fibers to the abdominal viscera. Autonomic fibers are also supplied to the bronchial tubes, esophegus, stomach, pancreas, gall bladder, small intestine and ascending colon.

(XI) The accessory nerve (a motor nerve) is composed of two parts, a cranial and a spinal portion. The cranial part arises from a nucleus in the medulla and emerges from the side of the medulla just below the roots of the vagus. The spinal part arises from the spinal cord in the upper cervical region and ascends, passing upwards through the foramen magnum. The cranial portion is accessory to the vagus and supplies most of the pharyngeal and laryngeal muscles.

(XII) The hypoglossal nerve is a motor nerve distributed to the muscles of the tongue. It arises from the medulla. Injury to this nerve causes difficulty in speaking or swallowing.

SPINAL CORD

It is ~~that~~ a part of central nervous system within the vertebral canal. It is continuous with the base of the brain anteriorly; posteriorly it tapers to a threadlike strand below the second lumbar vertebra. In the early fetus, the spinal cord extends the length of the spinal canal, but as the fetus grows, the vertebral column grows in length at a greater rate than spinal cord. Hence the cord is drawn forward in the vertebral canal and the roots of lumbar, sacral and coccygeal nerves travel down the spinal canal to reach their normal places of exit. The taillike group of nerves is called cauda equina.

The cord is suspended rather loosely in spinal canal. Since its diameter is considerably less than that of canal, the vertebral column can be moved freely without injury to the cord.

Conduction Pathways of the Spinal Cord

Some ascending tracts - the vertical neurons of the cord are arranged in orderly bundles. Two of the large posterior ascending tracts are the fasciculus gracilis and fasciculus cuneatus. The cell bodies of the neurons composing these tracts lie in the dorsal ganglia of spinal sensory nerves and their fibers extend upward to the medulla ending in the nucleus cuneatus. (A nucleus is a group of nervecell bodies within central nervous system) other neurons connect the nuclei and the thalamus, a third set of neurons conveys impulses from the thalamus to the sensory interpreting areas of cerebral cortex. This is the pathway by which the position of the muscles is interpreted and the sensatious of touch ar received.

Large tracts in the lateral part of the cord are direct cerebellar tracts. They are concerned with muscular coordination. Sensory impulses, may be considered as unconscious muscle sense, are conveyed upward to the cerebellum.

Spinothalamic tracts lie in the lateral and ventral portions of the white matter. These pathways convey impulses to the thalamus and then to the cerebral cortex where they may be interpreted as pain, temperature, pressure, touch and muscle sense.

Some Descending Tracts

The neurons composing the corticospinal tracts have their origin in the motor area of cerebral cortex. Most of them cross over to the opposite side in the medulla and descend in the lateral part of the cord. Hence the names crossed pyramidal tract or lateral corticospinal tract. The fibers that do not cross in the medulla form two small ventral columns called the direct pyramidal tracts or ventral corticospinal tracts. The neurons of both tracts make synaptic connections with the motor nerve roots of spinal nerves at various levels. The neurons of the direct pyramidal tract cross in the anterior white commissure just before they make synaptic connection with a spinal nerve root. These are the pathways of voluntary motor impulses to the muscles of the trunk, arms and legs. The direct pyramidal tract supplies muscles of the trunk; the crossed pyramidal tract supplies muscles of the arm and legs. About two third of the descending fibers cross over.

Extra pyramidal system involves greater area of the cortex, including supplementary motor area. Neurous of this system may synapse several times at subcortical levels (includes basal ganglia, red nucleus and reticular formation)before reaching a spinal motor outlet.

The rubospinal tracts (the cell bodies of whose neurous are located in red nucleus of the midbrain) descend through lateral part of the cord. Their fibers cross immediately and descend to various levels of the cord where they make connectios with spinal motor nerve roots. Since red nucleus has both cerebral and cerebellar connections, much of the voluntary muscle control may be transferred to involuntary muscle coordination over these pathways.

The Vestibulospinal tract originates from the nucleus of the vestibular nerve in the medulla. Since they receive impulses from semicircular canals of the ear, their function is

The main classes of retinal ~~nerveur~~ neurons are :

Receptors - (rods and cones) perform photodetection and thereby initiate the neural signal.

Ganglion Cells - transmit the visual information to the brain; the axons of ganglion cells form the optic nerve.

Bipolar Cells - make complex interconnections between receptor and ganglion cells.

Horizontal Cells- make lateral connections at the synaptic junctions between receptors and bipolar cells.

Amacrine Cells - make lateral connections at the synaptic junctions between bipolar and ganglion cells.

Except these basic neuron classes, there are a number of different types - such as mopbipolar cells, midget ganglion cells etc. The light passes through several neural cell layers, which are transparent, before reaching to the receptors (rods and cones) where photodetection takes place. Retina has glial cells also, in addition to neurons, which had been considered only to take part in metabolism but more recent evidences indicate that they play a role in neurological signal processing.

The optic nerve passes through a hole (blind spot) that is 15^{o} away from the fovea in the nasal direction. The combination of high sensory receptor density in the macula plus lower density toward periphery dictates the arching configuration of Fig. 3.1(b) to adjust muscular coordination in relation to maintaining equilibrium.

Spinal Nerves

Thirty one pairs of spinal nerves arise from the cord. They are grouped as - cervical 8 pairs, thoriac, 12 pairs, Lumbar- 5 pairs, sacral - 5 pairs, coccygeal - 1 pair.

Spinal nerves form cervical, brachial, and lumbosacral plexuses.

C H A P T E R - 3

HUMAN VISUAL SYSTEM

In order to go in for visual pattern processing and recognition in human brain we must, first, have an insight in the neural anatomy and physiology of visual system in brief.

Anatomy and Physiology of Visual System [1],[2],[4],[31]

The eye looks out upon the world and by a mechanism reports its details to the brain. How, exactly, the visual reports convert incoming light into nerve impulses and how brain interprets those impulses, is a perplexing problem in physiology.

The Fig.(3.1a) shows the major parts of human eye. The eye ball is nearly spherical. The wall of the eyeball is compose of three layers - the outer coat is fibrous tunic consisting of sclera and cornea. The intermediate layer is a highly vascular, pigmented tunic composed of choroid, a muscular body and the iris. The innermost layer is retina. The refracting media of the eye contains aqueous humor lens and vitreous body.

The sclera is a white layer of the eye. It covers the eyeball except the cornea and consists of a dense interlacing of white fibrous tissue. This opaque covering helps to maintain the shape of the eyeball and protects the more delicate structures from injury. The anterior surface is covered by conjuctiva.

Cornea is the transparent part of the sclera. It represents about one sixth of the total area. Astigmatism is usually caused by the imperfect curvature of the cornea.

The intermediate layer of the eyeball is composed of Choroid, ciliary body and the iris. The choriod is a dark brown membrane that lines the sclera and it is concerned with the nutrition of retina. Being dark it absorbs light rays and prevents reflection. Optic nerve passes through the choroid at the back of the eyeball.

By the ciliary muscles the eyelens adjusts its convexity. For close-up work as reading, ciliary muscles slacken and lens becomes more convex.

The iris is the most anterior portion of the choriod. It is highly coloured part of the eye. The eyes of human beings may be blue, gray, green or brown depending upon distribution of pigments. The circular opening of the iris is called the pupil. It appears black as it opens into the dark recess of the eyeball. The iris is anterior to the lens but posterior to the cornea.

The lens is a clear, transparent tissue located posterior to the pupil and iris. It is biconvex lens but somewhat more convex on the posterior side. The lens is able to change its degree of convexity during accommodation for near and far vision with the help of ciliary muscles.

Retina is the inner nervous tunic of the eye. It is light sensitive and extends about 240° around the inner circumference of the eye. This portion of the eye forms originally as a part of the lateral wall of the brain. The retina, though very thin, contains several layers of neurons, through which incoming light has to pass. Important of those layers are eight, namely-inner limiting, optic nerve, fibers, ganglia, inner plexiform, inner nuclear, outer plexiform, outer nuclear, and outer limiting. Only then the light reaches the actual light-sensitive receptors the rods and cones. The rods respond to all visible wavelengths whereas the cones respond individually with maxima in blue, green or red regions of the electromagnetic spectrum. So the rods provide only achromatic (black and white) vision and operate primarily at very low light levels The central 1° portion of the retina, called fovea, contains only cones and is the region of high visual acuity. Fovea is the subjective center of the optical systems. Here are 34000 cones (no rods) crowded into a disk (the macular) of about 1.2 mm (4°) in diameter. The radius of the disk, macula, is about 100 cones. The eight layers mentioned, are minimal in foveal region.

The center to center spacing between cones at fovea is .0023 mm, i.e. an angle of about 0.01° between the two rays of light that are focussed at adjacent cones. The experiments on visual acuity also show that an observer can resolve two point sources which are 0.01° apart (the angle seen from the observer).

The main classes of retinal ~~nerves~~ neurons are :

Receptors - (rods and cones) perform photodetection and thereby initiate the neural signal.

Ganglion Cells - transmit the visual information to the brain; the axons of ganglion cells form the optic nerve.

Bipolar Cells - make complex interconnections between receptor and ganglion cells.

Horizontal Cells - make lateral connections at the synaptic junctions between receptors and bipolar cells.

Amacrine Cells - make lateral connections at the synaptic junctions between bipolar and ganglion cells.

Except these basic neuron classes, there are a number of different types - such as mopbipolar cells, midget ganglion cells etc. The light passes through several neural cell layers, which are transparent, before reaching to the receptors (rods and cones) where photodetection takes place. Retina has glial cells also, in addition to neurons, which had been considered only to take part in metabolism but more recent evidences indicate that they play a role in neurological signal processing.

The optic nerve passes through a hole (blind spot) that is 15° away from the fovea in the nasal direction. The combination of high sensory receptor density in the macula plus lower density toward periphery dictates the arching configuration of Fig. 3.1(b)

Since colours remain faithful outside the macular region the ratio of one cone per fiber probably holds throughout the retina. The number of rods per fiber gradually increases from 1 near the macula to 250 at the periphery, where high sensitivity to changes in light intensity guards against sneak attacks.

Photodetection occurs in cylindrical outer segments of rods and cones. These outer segments are 1 μm in diameter and generally 25 μm long. Light that is not absorbed in the receptors is absorbed in the black pigment epithelium layer.

Human retina consists of 5 million cones and 125 million rods. A cone covers a much larger area than a rod and so retinal areas covered by rods and cones are comparable. There are about 1 million nerve fibers in the optic nerve, but electron microscope reports about 10 times this number in the frog regina which easily gives an idea of fibers in human retina. Rod and cone cells have essentially the same basic structure but rod cells are typically longer and more slender than cone cells.

The optic nerve pathways to the visual cortex are shown in Fig. (3.2). The fibers of the optic nerve are the axons of ganglion cells, the nuclei of which are in the retina. The optic nerves for the two eyes join in a cross-shaped structure called Chiasma, and then separate in two nerves called optic tracts. At the chiasma, half of the nerve fibers switch over, so that the right sides of both retinas are connected to the right side of the brain and left sides are connected to the left side of the brain.

The axons of ganglion cells in the retina extend through the chiasma to the left and right lateral geniculate bodies which occur at the underside of the brain. There they make synaptic connections with neurons that send their axons to the visual cortex and the lower back side of the brain. There are few fibers that leave the optic tract after the chiasma and go to the areas on the underside of the brain called pre-tected region and the superior colliculus. These are generally believed to be associated with pupillary reflex and eye movement respectively.

The images seen by both eyes are combined into one at lateral geniculate bodies. The single image is split into right and left halves, the left retinal fields (or right visual fields) going to the left hemisphere of visual cortex while right retinal fields are projected on right hemisphere. As the fibers are also split into upper and lower halves [Fig. (3.2)] it concludes that visual field is broken into quadrants. The upper and lower halves are also separated by the calcarine fissure of the occipital lobes. Despite the physical separation into four cortical regions, there is no obvious vertical or horizontal line discontinuity in normal vision. Association fibers bridge the gap between left and right hemispheres. The peripheral fibers serve various important auxiliary functions, and are not vital to reading, ability, so only 34000 macular fibers need be considered. While concerning with pattern recognition in visual cortex we reached this conclusion by reading through a hole that subtends 4° at the retina.

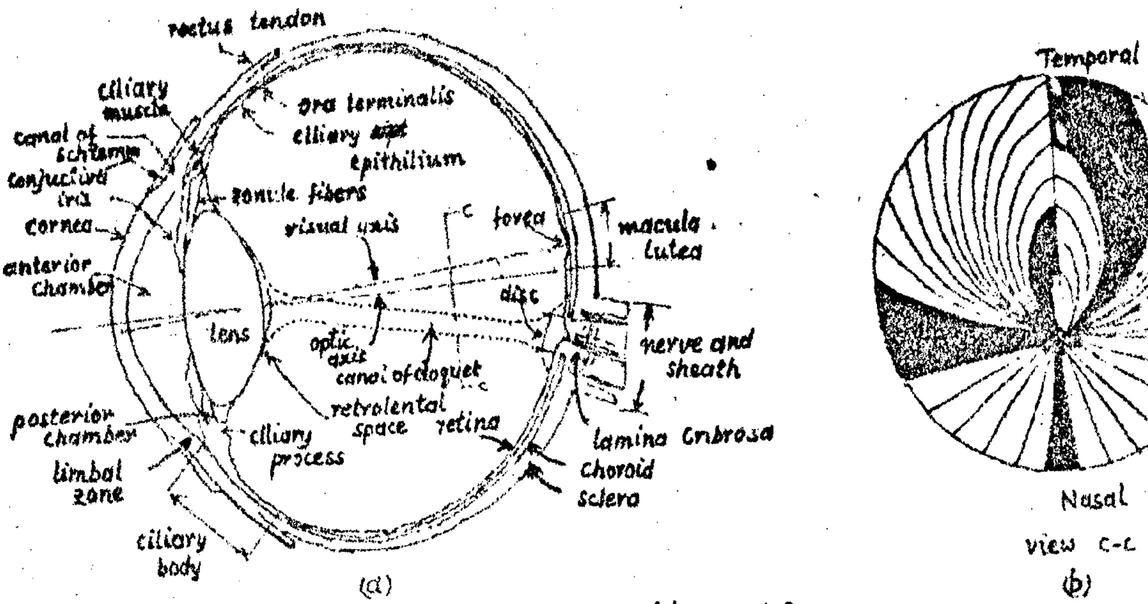


FIG-3.1 Horizontal section of human eye

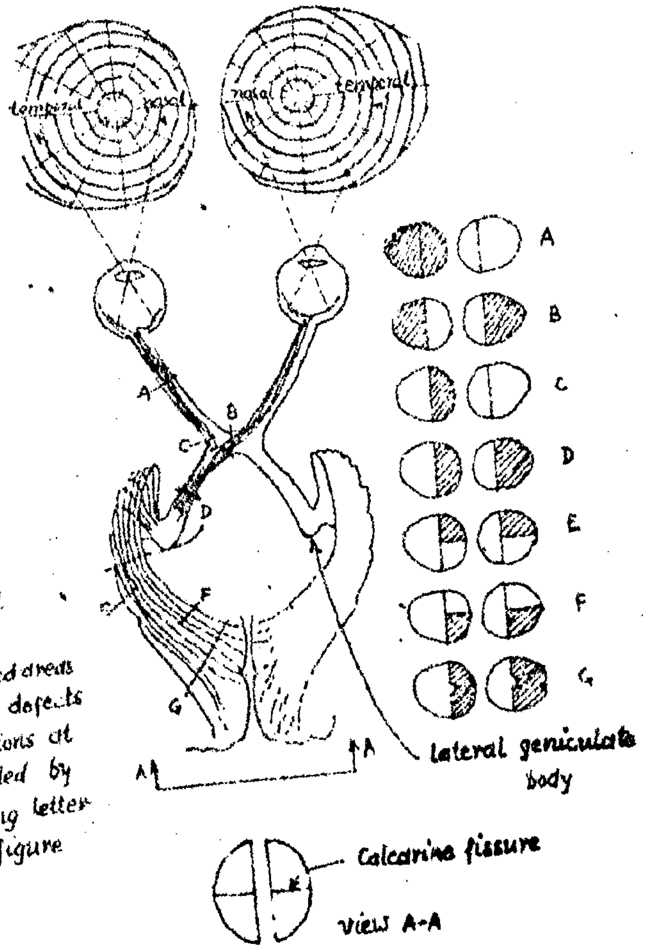


FIG 3.2 Central visual pathways to left hemisphere (Shaded areas show visual field defects resulting from lesions at the point indicated by the corresponding letter on left hand figure

Convergence between macular fibers of both eyes at lateral geniculate bodies takes place in a six layer neuron assembly, which can be explained as a scheme for maintaining colour fidelity when corresponding fields are superimposed in binocular vision. Blue fibers from the right eye are merged with the blue fibers from the left eye in the first two layers, green fibers merge in the next two layers and red fibers merge in the remaining two:

Most astonishing feature is how can a single cone handle such a wide range of stimulus amptitudes. To account for this wide dynamic rangeability four mechanisms are responsible -

1) A very obvious mechanism is pupillary light reflex that closes the iris in the presence of high average brightness. Average pupil diameter is given by

$$d = 5 - 3(B^{0.35}-1)/(B^{0.35}+1) \text{ mm} \quad B \text{ in candle/m}^2$$

The pupil diameter varies approximately from 2 to 8 mm and the middle value of 5 mm occurs at a brightness level of about 1 candle/m^2. This mechanism can modulate retinal intensity by a factor of 25 to 1.

2) There is enhancement of contrast between almost adjacent areas by appropriate release of inhibitory transmitters. It is believed that this may be the function of the horizontal cells of retinal structure.

3) Feedback signals from the brain to retina form synaptic junctions with the amacrine cells ~~which~~, which in turn excite or inhibit some areas relative to others.

4) A fast acting automatic gain control (AGC) changes the cone firing threshold to suit local intensity variations. The chief mechanism for AGC may be the depletion of colour-sensitive pigment in bright light and its accumulation in relative darkness. The iris, inhibitory and AGC devices extend cone-handling capacity of 1000 to 1 by a factor 10000, thus yielding an effective stimulus range 10^7 to 1.

Visual Threshold - One of the most important characteristics of human vision is its amazingly low threshold. Some typical values are given here:

Visual Threshold of the Human Vision

	Incident on eye
Rod vision-	
Brightness	0.75 microcandle/m^2
Retinal intensity	20 quanta/sec/deg^2
Power	100-150 quanta/sec
Energy	84-114 quanta
Power per rod	1 quanta/100 min.
Cone vision (fovea)	
Power	10000 quanta/sec
Energy	2440 quanta

These apply for conditions of maximum dark adaptation, the threshold is defined as the level at which a light stimulus is perceived 50% of the time. The photon values shown are the effective number of photons within the visible passband of the rod or cone. The energy threshold is measured with a narrow spot of light of short duration, the power threshold is measured with a narrow spot of light of long duration and retinal intensity threshold is measured with a broad light beam of long duration. About 50% of the light incident on the cornea reaches the retina and about 20% of the energy incident on the retina at the wavelength of peak visual response (507 mm for rods and 555 mm for cones) is absorbed in cones or rods. Thus the maximum quantum efficiencies (i.e. ratio of photons absorbed to photons incident on eye) for the rods and cones are both approximately equal to 0.1. So Rod threshold corresponds to the absorption of about 10 quanta. The cones require about 25 times as many quanta for threshold, which shows their higher noise level when the retina is receiving a light intensity corresponding to rod threshold, a particular rod absorbs a single quantum of light only once for every 100 min. The eye can tolerate without damage a quick look at the sun in the sky which has brightness greater than 1000 M cd/m^2 and visual threshold is less than 1 μ cd/m^2. Thus the brightness range between absolute threshold and retinal damage is greater than one million billion (10^{15}).

At reasonably high light levels the eye is capable of sensing very small differences in the intensity and spectral content of the light it receives when two large colour samples (about 10° field of view) are held side by side under good illumination, the eye can readily detect differences of 0.1% in spectral reflectance. It is so sensitive in this regard that the eye could discriminate among at least 10 million different colour samples.

Organization of Visual Cortex

Keeping in view the innumerable visual pattern to be processed and perceived by the eye, it is necessary to assume a hierarchical organization similar to the telephone dialing system. The first layer of visual cortex output neurous only processes simple pattern, such as straight lines and circles, in the next-layer the simple strokes give way to combination of strokes, such as letters of the alphabet, groups of letters, such as syllables are handled in the following layer, finally groups of syllables, or words are analyzed. Ideally a single neuron can stand for a letter, or a syllable or an entire word. Visual patterns are assumed to be time invariant.

Some Guyton quotations regarding visual cortex organization are given [~~Fig. ( )~~].

"Area 17 is the primary visual cortex, which lies almost entirely on the medial axis of cerebral hemisphere but extends out of the longitudinal fissure onto the outer surface of occipital pole. Area 17 is also called the striate area because of its striped appearance to the naked eye. Area 18 lies immediately above and lateral to the visual cortex and area 19 lies still further above and lateral to area 18" .

"Electrical stimulation in the primary visual cortex, area 18, or area 19 causes a person to have optic auras - that is, flashesof light, colours, or simple forms such as stars, disks, triangles and so forth-but he does not see complicated forms".

"Stimulation of the temporal cortex on the other hand often elicits complicated visual perceptions, sometimes causing a person to 'see' a scene that he had known many years before".

Widespread destruction of areas 18 and 19 decreases one's ability to interpret shapes, sizes and meaning of objects, and can cause particularly an abnormality known as alexia, or word blindness, which means that the person can see words perfectly well but cannot identify their meanings. Destruction of cerebral cortex in the angular gyrus region where the, parietal and occipital lobes all come together usually makes it difficult for a person to correlate visual images with the motor functions. For instance, he is able to see his plate of food perfectly well but is unable to utilize the visual information to direct his work toward the food, yet, if he feels the plate with his other hand, he can use stereotaxic information from his somesthetic cortex to direct the fork accurately".

Visual Perception (A Theoretical Approach)[9],[10]

Before proceeding to the visual pattern processing and recognition in human brain, we should have an understanding of the theoretical aspects of visual perception. Some important questions are here before us to seek explanation. How patterns are learned or committed to memory? How these pattern are recognized when subsequently encountered? How patterns are recognized under unfavourable, real world conditions ? when they are distorted, enlarged or rotated or viewed along with other patterns in a cluttered and noisy visual field? The patterns are stored in the memory as a network of memory traces which represent the features of the pattern and the attention shifts may take the form of sac cadic eye-movements or internal eye movements which are less than $1/2^{0}$. Thus memorising and recognizing a pattern are closely analogous to memorising and repeating a conventional sequence of behaviour each being an alternating sequence of sensory and motor activities. During pattern perception this theory gives a clue of the presence of scanpath. Thus learning a pattern is similar to constructing an internal representation of the pattern in the memory while recognising a pattern is analogous to finding the internal representation of the pattern in the memory. During recognition the matching of the pattern is guided by the internal representation which directs attention from feature to feature of the pattern. Every individual develops his own way of sequencing in tracing features of each pattern and this way of sequencing i.e. the scanpath is largely affected by the habits of the individual.

Eye and Visual Cortex

The combined system of eye and visual cortex senses the visual field and extracts and processes useful information from that. It is assumed that the visual cortex detects simple features as lines and angles and the feature detection beyond this stage proceeds allowing somewhat more complex elements of a pattern to be detected and considered as features or primitive elements. The notion of the recognition of a pattern is based on the presence or absence of each detectable feature at each location in the visual field which is extracted by visual cortex and supplied to recognition system. A noteworthy point is that feature detection is not uniform throughout the visual field but it is more detailed and precise near the centre of fixation (that part of the visual field which is imaged on the fovea) and only gross features are detected at the imprecise locations at the periphery of the visual field. The centre of fixation is shifted from one point to other in the visual field by rotating the eye. The movement of the eye is continuous. In normal operation the eye alternates, stationary periods fixations, with fast rotational movements, saccades which move the centre of fixation to new locations in thevisual field.

The recognition system at one time inspects only feature or features detected by visual cortex in small area of the visual field. The centre of attention is usually, though not always, close to centre of fixation. The recognition system shifts the centre of attention to different places in the visual field but this does not always shift centre of fixation. An attention shift of large angular displacement 5^{o} or more takes the form of saccadic eye movement unless the crude feature detection in non-foveal region of the eye is acceptable, while a small angular attention shift (less than $1/2^{o}$) may be carried out internally without moving the eye, the centre of fixation simply moving to a new point of the visual field in the neighbourhood of centre of fixation.

Memory System

The internal representation of any pattern in the memory consists of sensory and motor memory traces which are the records of past sensory and motor activity. These records are connected by undirectional links indicating the order in which different activities occurred. So a chain of sensory and motor memory traces can record an interactive sequence of events, a sequence of sensory situations and motor activities which transformed each into the next. The memory traces are normally inactive but during recognition as one of the memory sensory situation is excited due to attention mechanism, all sensory memory traces recording previous occurrences of that situations are activated associatively. These active traces are now available to the recognition system which can propagate the activation by means of connecting links.

Learning or memorizing a previously unknown pattern for its recognition in future, is a process of constructing in the memory an internal representation of the pattern. Thus memory system must contain a model or internal representation for each pattern which is to be recognized. For larger and complex patterns the internal representation of its sub-pattern in the memory associate in an orderly sequence and the recognition of final pattern thus takes place. Internal representation of the pattern in the memory is equivalent to the feature network of sensory and motor memory traces, the sensory traces represent and record features of the pattern and the motor traces recording the attention shifts to scan all the important features of the pattern ~~form~~ from one featufe to the other across the visual field.

The feature network is a description of the pattern in terms of its features and relatfve locations. It is a way of breaking down the pattern into manageable, memorizable peices and an integration of these peices represents the pattern as a whole. If an unknown pattern is presented before a person, he exploros,investigates and analyzes the pattern through attention shifts from one feature to other and tries to find its equivalent in the memory but absence of its equivalent in memory makes the person to get acquainted with the features of the pattern and a feature network in the memory is formed which contains record of features as sensory traces and attention shiftsfrom feature to featuwe as motor traces. The feature network does not include all possible attention shifts between features but only those which occurred with some frequency.

Recognition of a Pattern

Recognition of a pattern is the process of finding a feature network in the memory which is a representation of the pattern or which matches the pattern. It is a sequehtial process we match the features of the pattern and memory feature network feature by feature.

As a pattern appears in the visual field, firstly attention is fixed at any feature at random. This feature activates sensory traces in the memory, in one or more feature networks, the potential matches for the pattern and one of those networks is arbitrarily selected for matching. The recognition system now attempts to match feature network and pattern feature by feature through attention shifts. The sequence of matching features is guided by the memory feature network and verifies the successive features called for by the network. If the network is in fact a correct match for the pattern, then all the features will correspond and the pattern will be successfully recognized. If the network is not a correct match for the pattern then recognition system will sooner or later fail to find the feature expected at some location. The recognition process is then aborted or reinitiated either using another of the feature networks originally activated or restarting entirely with the most recently processed feature. Such mismatches and restarts can be greatly reduced by expanding the sensory memory traces to record not only the feature which the current object of attention but also a few gross features detectable peripherally at the same time. This reduces the number of memory traces which match and are activated by the sensory situation at the initial location of the attention and increases the probability of a selecting a correct feature network for matching with the pattern. It also reduces time taken for recognition. It is proposed that such expansion of sensory memory traces to record peripherally detectable gross features occurs gradually as the pattern becomes well known and its feature network becomes well established in the memory. If, and as proposed, we consider features corresponding to sensory situation and attention shifts corresponding to motor memory traces, memorizing a pattern becomes analoguous to memorizing a conventional sequence of behaviour and recognizing a pattern is analogous to repeating this sequence of behaviour. So memorizing a pattern involves recording in memory a sequence of sensory situations, the features of the pattern and attention shifts from each feature to the next and analogously memorizing a conventional sequence of behaviour involves recording in memory a sequence of sensory situations and the motor activities which transformed each situation into the next. Similarly, in the recognition of a pattern each verified feature leads to a motor memory trace i.e. attention shift which passes to the next feature and analogously in the repetition of a sequence of behaviour each previously experienced sensory situation leads to the motor activity which brings about the next sensory situation. So pattern perception and behaviour seem to ~~be~~ proceed in a closely analogous fashion and require same type of memory system.

It looks, in a way, habits play an important role in the pattern perception as they do in behaviour. A behaviour habit may be considered to be a sequence of preferred responses to a sequence of sensory situations. In terms of perception theory, this becomes a habitually preferred path which is followedthrough the feature network when proceeding from feature to feature during memorizing or recognizing.

This path is referred to as scanpath. Each person develops his own characteristic habits of behaviour, so each can be expected to develop his own characteristic scanpath for each pattern, he can recognise. The scanpath will be different for different patterns and for a given pattern scanpaths will differ from person to person. The scanpath is fixed and characteristic for a given person viewing a given pattern.

<u>Recognition Under Unfavourable Conditions</u>

The real world patterns and three dimensional objects are to be perceived under various unfavourable and confusing situations or conditions:

1) Pattern may be presented to the eye in a transformed version, enlarged, diminished, translated or rotated, often as a result of its position relative to the observer (though in practice humans show only a limited ability to recognize rotated patterns.

2) ~~Patterns~~ Pattern may be a distorted version of a known pattern or it may be similar to the known pattern and should be recognized as such.

3) Pattern is generally observed in presenceof other patterns (clutter) or irrelevant visual stimuli (noise) which form a confusing background amdist which the pattern must be recognized and isolated as a separate entity.

To recognise a pattern one must first ignore the irrelevant and confusing back ground, since the visual field is processed as a whole, without selective attention, but to know which features form the irrelevent background one must already have recognized and isolated the pattern. By proceeding sequentially with attention directed by feature network, the proposed perception process steers a middle course through this dilemma. If a visual field contains one or more known patterns together with miscellaneous background noise and the visual attention falls initially on the feature of the pattern, then recognition proceeds in a normal way from feature to feature through the feature network, the feature network directs the attention from one feature to the other feature thus avoiding the effect of noise and clutter. The pattern is thus recognized and isolated getting rid of other patterns in the visual field, which may now be subjected to the same process again, to seek out other patterns. If somehow the initial attention falls on, the noise feature or clutter, then whatevver matching will be tried, will fail and process will start with a new feature, thus encountering and recognizing all patterns the visual field, contains.

Acceptance of certain degree of inaccuracy is essential while recognizing distorted patterns i.e. accepting a feature slightly different from that specified in a sensory memory trace or at a location slightly different from that specified by the attention shift in the motor memory trace. The degree of inaccuracy must of course be controlled and should not be accepted beyond a limit since exessive tolerance will allow any pattern to match any feature network. Translated (shifted) patterns require no special handling, once the visual attention has fallen on a feature of the pattern, making with the feature network involves only relative locations of the remaining features, rather than their absolute locations.

A uniform scaling factor is applied to recognise enlarged or diminished pattern to each attention shift, called for by the feature network, the scaling factor being determined at the time of first attention shift. Similarly, rotated patterns require that a uniform rotation be applied to each attention shift. These adjustments will match the locations of the features with the locations dictated by feature network but the features themselves having been enlarged, diminished or rotated as a parts of the pattern will not match directly with the features specified in the sensory memory traces. The simplest features, lines and angles are infact scale invariant by nature but in general it is necessary to assume that feature detection process is scale invariant (as regards more complex features) and rotation invariant (to the extent the recognition is).

Some Other Considerations - Multiple Levels of Internal Representation

The feature network for a very complex pattern would contain very many memory traces and be ~~im~~unmanageably complex. e.g. Image Such complex patterns may be tackled by two level (or many level) feature networks. The upper level network break the pattern down to less complex subpatterns each of which is then represented by a normal network of manageable complexity, on the lower level. Consequently the upper level network records the overall impression of the pattern and the lower level network records the details. In fact there are many problems of perceptions e.g. use of context, the recognition of many basically similar objects each with minor distinctive features etc.) which are simplified by assuming many levels of internal representations. This approach leads eventually to the concept of the organism equipped with a complete hierarchically organized model of its environment, the feature networks of the present theory being simply the lowest level of its hierarchy.

Recognition of Well Known Patterns

As pattern becomes well known each sensory memory trace in the feature network expands to record not only the feature associated with current object of attention but also some gross features detectable peripherally at the same time. As a result of this process recognition of a well known pattern may gradually become possible without completing the scanpath and verifying all features ultimately with a very simple or distinctive pattern, the first fixation of attention may suffice for recognition. In a sequential recognition process there is no exact point at which recognition may be said to occur but rather there is a gradual build up of certainty as each feature is verified.

High Speed Recognition

Any sequential pattern recognition theory must face the problem of high recognition speeds of which humans are capable. If attention shifts take the form of eye movements, not more than four or five fixation are possible per second, however, internal attention shifts are not subject to mechanical inertia and proceed at neural speeds. In this way with the help of additional short term memory tachistoscopic recognition seems explicable within bounds of the theory.

Three Dimensional Objects [29]

The internal representation of a three dimensional object is simply a feature network recording three dimensional features and three dimensional shifts of attention and this is matched with a three dimensional object during recognition in the normal manner.

CHAPTER - 4

PERCEPTION OF COLOUR [4]

The problem of colour vision has intrigued man for centuries and several models have been proposed to explain colour vision process. The immense interest of this field fetched is due to its extensive industrial use in colour-photography color pr nting, color television and the manufacture of colourants for dyes, paints, plastics etc.

In the industries we have to search for a tolerance in colour for its proper perception smaller the tolerance costlier the control process. So we have to optimize this tolerance for the cost of control. Different formulas have been proposed for this colour tolerance. In this context it grows of utmost importance to have a better understanding how in humans the colours are percieved. It would be very helpful to have a model of human colour vision that could quantitatively predict colour discrimination capabilities of the eye under practical viewing conditions but no such effective model exists. So there has been great need for theoretical models of colour vision which integrate the experimental data into a consistent frame of reference. There are some general models, particularly the trichromatic model of Thomas Young that have been useful as a frame of reference for generalizing experimental data. Bartlett and Graham [ ] have given very good general discussions colour vision for deeper understanding of this complex area of colour vision. Discussions of colour vision directed particularly to the physicist have been given by Sears [illegible] and Feynman [illegible]. More detailed information with emphasis on the practical aspects of colour theory is given by Evans Judd and Wyszecki [—], Bellimeyer and Saltzman [—]. The development of colorimetry is discussed in detail by Wright [—], who performed the colour-making experiments on which the modern system of colorimetry is based. An excellent collection of ~~experts~~ excerpts of major source articles concerning models of colour vision have been provided by Teevan and Birney [—]. Critical evaluations of colour vision models and the agreement or disagreements between these models and experimental evidence have been provided by Balarman and Sheppard [—]. Sheppard's report is directed toward the engineer and physicist.

Models of Colour Mixture

Newton discovered that aprism separates white light into its spectral colours. In 1672 he proposed that light consists of particles of different size which decrease in size from red to the violet end of the spectrum. These particles when impinge on retina, induce vibrations of different frequencies and these vibrations are transmitted to the brain through optic nerve and accordingly, colour sensations are produced. Newton also proposed a colour circle which described the effects of mixing colours. The colours for narrow-band lights were placed on the perimeter of the circle. The colour of a mixture of light is determined from the diagram by a 'Centre-of Gravity' calculation based on the coordinates of the individual lights in the mixture.

In 1801 Young, proposed the trichromatic model, which is the basis for practically all of our modern models of colour vision. He proposed that retina has three types of photodetectors with different spectral responses, and that signals from these photodetectors are sent to the brain to provide colour sensation. These three photosensitive detectors are usually assumed to be primarily red sensitive, green-sensitive and Blue sensitive. This hypothesis is based on the fact that colour samples can be arranged into a three dimensional array in terms of colour sensation they evoke. Maxwell clarified, that Young's fundamental contribution was to recognize that this three-dimensional character of colour was the result of the way the eye perceived the light, and was not the result of the characteristics of the pigments reflecting the light, or of light itself. In other words, colour is three-dimensional because the eye perceives colour in three ways, and not because there are any three dimensional aspects of the spectral characteristicsof the light itself. Young explained this three dimensional property of colour vision by proposing that the retina has three types of photodetectors with different spectral responses

After half a century, Maxwell and Helmholtz, almost at the same time, keeping Young's theory the basis, developped further the aspects of colour vision. Maxwell performed crude psychological experiments to measure colour-matching properties of the eye. Helmholtz explored the colour matching of the eye much more thoroughly and elaborated Young's simple model extensively and built a more detailed colour vision model called Young Helmholtz theory.

The Young's model provided a precise theoretical foundation, which was lacking in Newton's somewhat arbitrary calculations. The foundation yielded a mathematically consistent set of hypotheses for colour mixture which could be related to psychological experiment for verification. According to the Young's model, the retina detects three colour signals, which are designated as R, G, B that can be expressed as

$R =$	$\bar{r}(\lambda)I(\lambda)d_\lambda$	where $I(\lambda)$ is the received light spectrum
$G =$	$\bar{g}(\lambda)I(\lambda)d_\lambda$	$\bar{r}(\lambda)$,$\bar{g}(\lambda)$and $\bar{b}(\lambda)$ are the spectral respons
$B =$	$\bar{b}(\lambda)I(\lambda)d_\lambda$	~~to~~ of the three photodetectors in the retina.

If two light spectra have the same R, G, B values they are indistinguishable to the eye.

The assumption goes that we cannot learn directly from psychological experiments as what are the spectral responses $\bar{r}(\lambda)$, $\bar{g}(\lambda)$, $\bar{b}(\lambda)$ of the three photosensitive elements. However it can be shown that colour matching experiments can yield spectral responses that are linear transformations of $\bar{r}(\lambda)$, $\bar{g}(\lambda)$, $\bar{b}(\lambda)$ where the constants of transformation are unknown Fig. (4.1) shows spectral responses for standard human observer that are used in colourimetry. These curves were standardized by CIE (International Commission on Illumination). These were derived from colour matching experiments and are designated as $\bar{x}(\lambda)$, $\bar{y}(\lambda)$, $\bar{z}(\lambda)$. From these values tristimulus values X, Y, Z can be calculated for any given spectrum $I(\lambda)$ as follows:

$$X = \bar{x}(\lambda)\ I(\lambda)d_\lambda$$

$$Y = \bar{y}(\lambda)\ I(\lambda)\cancel{d_y}d\lambda$$

$$Z = \bar{z}(\lambda)\ I(\lambda)d\lambda$$

According to the Young Model $\bar{x}(\lambda)$, $\bar{y}(\lambda)$ and $\bar{z}(\lambda)$ are linear transformations of retinal spectral responses $\bar{r}(\lambda)$, $\bar{g}(\lambda)$, $\bar{b}(\lambda)$. The tristimulus values X, Y, Z are linear transformations of the three signals R, G, B formed in the three photosensitive elements in the retina. So two light spectra have same values of X, Y, Z are indistinguishable to the human eye. Laws of colour mixture as followed from Young's Model are as follows:

1) <u>Trivariance in Colour Matching</u> : The eye can match in colour any light (sample) by using appropriate amounts of three suitably chosen standard lights called primaries. In making this match it is often necessary to add one of the primaries to the sample light and match this mixture against a mixture of other two primaries. These primaries must be chosen so that mixture of the two primaries cannot match the colour of the third.

2) <u>Constancy of Metameric Match:</u> If two lights match in colour under one condition of the adaptation of the eye, they will match under any other condition, even though the colours that are evoked in the eye may be different in the two adaptation conditions. (Two lights that match in colour but have different spectra are called metamers.

3) <u>Associative Law:</u> If light A matches light B in colour and light B matches light C, then A will match light C.

4) <u>Law of Additivity:</u> If light A matches light B and light C matches with light D, then mixture of A and C will match mixture of B and D.

5) Multiplicative Law: If light A matches light B, a light with the same spectrum as A but K times intensity will match a light with the same spectrum as B and K times the intensity. Multiplicative law is actually a direct consequence of the Additivity and associative laws. The tests of laws of the color mixture, established by Maxwell and Helmholtz have been repeated by other researchers with greater accuracy.

It is possible to postulate a limitless family of models of colour vision which satisfy the basic Young model. Thus the Young model allows a very wide variation of physiological detail and of the processing of the trichromatic spectral data to form colour sensations. Practically all the models of colour vision of last century, as shown by Wright and Judd, satisfy the Young trichromatic model.

The fundamental premise underlying the general acceptance of the Young model is that the laws of colour mixture have been verified experimentally. Biernson shows that these laws hold approximately and introduce a degree of error at higher accuracy. A serious problem in evaluating the accuracy to which the laws of colour mixture hold is that the eye is extremely accurate in comparing spectra that are nearly alike but experiences great variability when matching colours if the spectra is radically different. Therefore it looks quite difficult and complex how error and variability in colour matching should be interpreted.

Biernson has postulated a model of colour vision which follow Young model and so disobey laws of colour mixture to some extent. As it satisfies laws of colour mixture to first approximation, it appears to be consistent with experimental evidence. The receptors, according to one assumption, sense nearly full spectrum of received light and the retina processes this full spectral data in performing visual adaptation. The processed data is then reduced to three colour signals. Since this model has much more spectral information available for retinal data processing then does the Young model, it is theoretically capable of more accurate spectral discrimination and much greater insensitivity to changes of illumination.

Models of Colour Sensation

Colour vision process is an amazingly complex process as felt by researchers of late 19th century. Young Helmholtz colour vision model failed in many respects to explain colour vision process, was felt by Hering. In particular, Hering recognized that we perceive colour as mixtures of six basic sensations red, green, yellow, blue, white and black. These six sensation form three opponent pairs, red-green, yellow-blue and white black. At one time only one sensation of a pair can be experienced so one colour of the pair acts as the negative of the other. Thus we experience either red or green but never a reddish green, we experience either yellow or blue but never a yellowish blue. We perceive the combinations of red and yellow (orange), Yellow and green (olive), green and blue (aqua), blue and red (violet). We also perceive various amounts of black and white mixed with these chromatic colours which provides tints and shades of colours. So it was postulated that these three opponent colour combinations are fundamental colour sensations of human vision. Fig(4.2)

Judd derived spectral responses of Hering opponent-colour sensations from colour-mixture data as shown in Fig. (4.3). As spectral responses vary with adaptation conditions, these are regarded as approximations. We perceive orange when both red and yellow signals are strongly excited and violet when both blue and red signals are strongly excited. The wave-length where blue-yellow signal~~s~~ is zero is designated G because this corresponds to pure green sensation. The two wave-lengths where red green signal is zero are designated Y and B because these correspond to pure yellow and blue sensations respectively.

Hering model is consistent with basic Young model but does not agree with the more detailed Young-Helmholtz elaboration of the Young model. Incorporations of Young and Hering models called, stage or Zone theories, use three types of photo-detectors of different spectral responses and develop at a later neurological stage three-opponent-colour signals of Hering model. Thus Young model describes 'process of excitation' and Hering model 'process of sensation'.

It was originally assumed that a red sensation was produced by certain wavelengths and a green sensation by other wavelengths but Hering showed that visual adaptation processes are so extensive that there is no direct correspondence btween a particular light spectrum and the col ur sensation it evokes. Visual adaptation acts as a regulatory process which modifies the response of the visual system so as to compensate for variations of illumination. The result is that the colour of an object generally appears to remain constant practically despite very large changes in the intensity and the content of the light reflected from the object to the eye, as the illumination on the object changes.

In his theory Hering did not give clear explanation about grey and he simply thought it as a mixture of white and black sensation. Dimmick recognized that grey is entirely different from black and white or their mixture. At the origin of the perceptual coordinates, the black-white sensation is zero so we experience pure grey. With increased lightness one perceive less grey more white, while with decreased lightness we perceive less grey more black. Later on Wallach and Evans also supported Dimmick's theory of grey sensation being entirely independent of black and white. The luminous perception provides the glowing appearance of light blulbs, the shiny appearance of gold and silver and the luminous character of brightly lighted areas. The grey perception providès the grey character of shadows and the greyness content of object colours.

By examining the appearance of a small spot of light of one intensity surrounded by much larger area of different intensity Wallach demonstrated his luminous-grey hypothesis. When small spot was brighter than the background, the spot appeared white and the background grey. When the spot was dimmer than the background the spot appeared black and the background had a glowing or luminous appearance quite distinct from white.

Evans and Swenholt have also recently investigated the luminous grey or fluorescence-grey sensation by some psychological experiments.

In the colour Television model of colour vision Young and Hering concepts have been implemented in colour television broadcasting. Colour Television camera and broadcasting system operates lik a stage model of colour vision. It employs three photodetectors with different spectral responses in accordance with the Young model and processes the signals from those photodetectors to form white-black, red-green and Yellow-blue opponent colour signals, following the Hering model.

In the transmitter of colour television, we employ three camera tubes which receive images from the scene filtered by red, green and blue filters. These scanned signals by a circuit are ~~of~~ converted to their appropriate mixture incorporating sums and differences. The outputs from this circuit are white-black, yellow-blue, red-green opponent-colour signals. Certain modulation techniques convert these signals into r.f. signals which are then broadcast. Television receiver detects the three opponent colour signals and recombines them in a netwo to recreate the basic red, green, or blue signals. These signals are used to drive the red, green and blue electron guns of colour picture tube.

The advantage of colour television over white-black type is that white-black signal is transmitted with a wide bandwidth, thered-green signal with a narrower sandwidth and yellow-blue signal even narrower bandwidth. This provides optimum use of available television bandwidth and allows a hi h resolution colour television signals to be transmitted over the same bandwidth used for black and white television.

E.Q.Adams proposed a colour vision model in 1923 which provided a useful frame of reference in a research to improve the spacing of colour chips in the Munsell atlas of colour. The retina has red, blue and green-sensitive cones. The effective stimuli detected by these receptors (R, B, G) respectively) which represent the light power falling within the spectral passband of the particular retinal cone. The neural signals, V_R, V_B and V_G have a nonlinear relationship with the effective stimuli R, B and G and the visual adaptation conditions of the cones, the relationship being

$$V_r = \sqrt{R/R_{av}}\ ,\ V_g = \sqrt{G/G_{av}}\ ,\ V_b = \sqrt{B/B_{av}}.$$

where R_{av}, B_{av} and G_{av} is the average stimulus of R, B and G to which different cones are adapted. This nonlinear relationship between R, G, B and V_r, V_g, V_b is postulated to be the same as between reflectance and perceptual scale of lightness (Munsell value). Further postultion is that the signals V_r, V_g and V_b are combined linearly to produce opponent colours signals according to Hering.

Adams related his model to the colour matching data of colourimetry. He assumed that three types of cones had the $\bar{x}$, $\bar{y}$, $\bar{z}$ spectral responses shown in Fig. (4.1). The neural signal of the three types were then

$$V_x = \sqrt{X/X_{av}}\ ,\ V_y = \sqrt{Y/Y_{av}}\ ,\ V_z = \sqrt{Z/Z_{av}}$$

where X, Y, Z are the tristimulus colorimetry values of the light reflecting from the particular colour sample under standard (day light) illumination, and X_{av}, Y_{av}, Z_{av} are the tristimulus colorimetry values of light reflecting from a white standard used as background for different samples.

Then red-green, blue-yellow, white-black apparent colours signals are

$$\begin{aligned} \text{red-green} &= (V_x - V_y) \\ \text{blue-yellow} &= (V_z - V_y) \\ \text{white-black} &= V_y \end{aligned}$$

Plots of (V_x-V_y) vs. (V_z-V_y) for Munsell colour samples which were presumed to correspond to the perceptual red-green, and yellow-blue colour sensations experienced by human observer, are plotted. So uniformity of perceptual spacing for colour chips would be achieved if their coordinates on the plot of (V_x-V_y) Vs (V_z-V_y) were uniform.

Some Physiological Models of Three Cone Three Photopigment for Colour Discrimination

It was postulated in previous models that retina contains three types of cones with different photopigments having different spectral responses. For several years psychological and physiological experiments, even under electron microscope, these three types of cones could not be detected. Although there is a great deal of complexity in the neural interconnections of the retina, no three way organization of the connections between cones and bipolar cells has been discovered. In birds retina only one type of cone - photopigment had been found called idopsin. As was found that the regeneration time constant of rods was four times to that of cones but no difference in regeneration time constants had been observed among the cones. Attempts to distinguish among cones by stimulating retina with microscopic points of light was unsuccessful. Rushton in 1957, by illuminating eye with varying wavelength measured the small amount of light reflecting from the black layer behind the retina (Photopigment eipthelium) and produced first positive physiological evidence in the direction of different cone types detection. He then bleached the retina with a strong light and repeated the experiment and then found the difference spectra (i.e. the difference between the spectra of the two cases). Finding the difference spectra for varying wavelengths of bleaching light he decided that the response peaks in red and green regions are produced by red and green photopigments. But third type (blue) photopigment was even undetected. Brindley and Rushton again conducted the experiments, in which retina was illuminated in the reverse direction by shining a bright light through the white sclera, in order to determine ~~if~~ whether the previous spectral responses were produced by different photopigment or by different filter effects in the retina. By matching the colour of this light with that of the light through the pupil, they were able to perform crude colour matches but only in the long wavelength half of the spectrum. They found that the colour match was achieved when the wavelengths for both the directions were same. So it was concluded that colour discrimination cannot be the result of filter effects in front of the receptors, so is due to photopigments.

Marks and Mac Nichol first conducted spectrophotometer measurements on the cones of dissected fish retina and then on human retina, Here again transmissivity spectra of an individual cone is measured before and after bleaching the cone with light and difference spectrum was obtained. This difference spect~~ive~~ra classified many cones into three groups with peak responses in yellow, green and blue regions of the spectrum. Waveguide ~~middle~~ model [5] cones being of very small diameter (few wavelengths of light), light interference occurs in cone and light intensity varies within the cone with radial distance, with axial distance and with angle about the axis. These intensity patterns with varying wavelength change. Also the light radiated out through the side of cone and so the proportion of the light power propagating within the cone varies with wavelength. Colour discrimination may be achieved by sensing variations in the light intensity within the cone or by sensing total power propagating in the cone.

Cones being of small diameter may be considered as wave-guides. Considering small taper of cones it is convenient to study the complicated optical wave effects within retinal receptors in terms of modes of a dielectric cylinder. Enoch examined the light emanating from the tips of retinal receptors and found it to exhibit mode patterns and he related these patterns to the theoretical one obtained by Snitzer obsterberg.

Enoch found that the mode patterns were remarkably stable with variations of wavelength and in many cases did not change when the wavelength ~~work~~ was varied over the visible band. No receptors are definitely not homogeneous dielectric structures, otherwise the patterns would change drastically with wavelength. Enoch has given a detailed summary of research associated with optical properties of the receptors and of models of vision based on his work. Schroeder in 1959, proposed a model of colour discrimination in which a single cone detects full colour information by measuring the axial variation of light intensity in the outer segment.

In 1962, Myers proposeda colour discrimintion model in which the diameters of the outer segments of cones differ from cone to cone. This would produce a difference in spectral responses of the cones, because a variation in diameter changes the amount of light that radiates out the side of the cone. Biernson[5] has postulated that a single cone obtains full colour information by sensing the radial variation of light intensity within the outer segment of the cone. Biernson and Synder, based on the analysis of mode excitation in the cones, have shown that the radial variation of light intensity has the appropriate pattern and spectral response characteribtics to provide colour discrimination qualitatively consistent with that of human vision.

Waveguide-mode evidences provide reasons to question the assumptions

1) the retina has three types of cones with different spectr characteristics
2) the difference in spectral response in caused by three types of cone pigments.

Biernson and Synder have shown that the spectrophotometer experiments on individual cones have not proven that retina has three types of cones. The evidence suggests that the cones tend to lock onto different mode patterns as they are bleached, the particular pattern varying with the initial bleaching condition of the cone. If this occurs, identical cones would exhibit different spectral responses with peaks in the yellow, green, and blue regions of visible spectrum depending on what modes they happen to accentuate. They have shown that the mode excitation process in a cone can vary strongly. With the pattern of photopigment bleaching. This could cause identical cones to lock out different mode patterns as they are being bleached.

Electrophysiological Experiment Model

Granit while measuring nerve impulse rates in the optic nerve found that when retina was stimulated with a varying wavelength, several types of spectral responses were obtained in different nerve fibers. Broad spectral response corresponding to black white sensation, was called by him as 'dominator' and several narrow spectral responses, called '~~modulzators~~ modulators'. He assumed that these were the direct spectral responses of individual cones and it was the basis for his 'dominator-modulator' model of colour vision.

Svaetichin discovered continuous voltages in fish retina called S potentials Mac Nichol and Svaetichin showed that certai S-potentials exhibit chrometer ic responses, which have one polarity at one wavelength and the other polarity at the other.

S-potentials corresponding to red-green and yellow-blue opponent colour signals have been found. An S-potential corresponding to the white-black signal was found not to change polarity with wavelength. So this theory provided strong support to the Hering model.

Land's Retinex Colour Vision Model

Land showed in 1959 that remarkably realistic colours can be achieved by projecting two black and white photographic images through coloured filters rather than three as normally used. Land accepted that his theory agrees with the classical colour theory of three types of cones which has at its base Young's model. Classical colour theory defines only colour equivalences of light spectra. It dictates that if a particular spectrum evokes a particular colour in a given situation, a different spectrum having same tristimulus values will evoke the same colour when displayed under identical conditions. It does not specify what the colour is.

Most of the theories and models of colour vision from Newton to Maxwell and Helmholtz assumed that there is a one-to-one correspondence between a given light spectrum and the colour sensation it evoked, but Hering showed that there is a strong effect of adaptation process of vision on the colour sensation and demonstrated that a particular spectrum could evoke radically different colour sensations under different states of adaptation. Adaptation contains slow or 'successive adaptation' and instantaneous or 'Simultaneous Adaptation'. Land emphasised that the major visual effects, he observed are essentially instantaneous and so are different from Hering's successive adaptation. Thus 'classical colour theory' in the strict sense does not predict what colours are perceived in ~~p~~ colour photography and so does not really apply to the two-colour projections of Land. To predict the colours perceived, we extend to 'Applied Colour theory'. It was found convenient to normalize the tristimulus values X, Y, Z relative to each other to find the trichromatic coefficients X, Y, Z, as

$$x = X/(X+Y+Z)$$
$$y = Y/(X+Y+Z)$$
$$z = Z/(X+Y+Z)$$

The relative values of x, y, z are not independent but related by $x + y + z = 1$. So a two-dimensional plot is adequate to represent the trichromatic coefficients. Such a plot is called chromaticity diagram. It is most commonly the plot y Vs. x as shown in Fig. (4.4).

By linear transformation of these variables several other chromatility diagrams can be drawn. In the Fig. solid outside curve the spectral locus, which was calculated from $\bar{x}$, $\bar{y}$ $\bar{z}$ spectral plots shown in Fig. (4.1). Values along the spectral locus curve are the wavelengths in nanometers. Each point on the two dimensional chromaticity diagram corresponds to a straight line through the origin in three dimensional plot of the X, Y, Z, tristimulus values. Along this line the ratios among X, Y, Z values are constant, coordinates on a chromaticity diagram remain constant if the intensity of light is changed keeping shape of spectrum same. So for each point on the chromaticity diagram, there is a whole family of spectra of the same shape but different intensities. The white point defines state of adaptation. Except under extreme illumination conditions, the eye perceives as being achromatic (white, black or grey) an object with a spectral reflectance that is flat over the visible range. Such an object reflects a light spectrum proportional to the spectrum of the illuminant. Therefore, the point on the chromaticity diagram corresponding to the spectrum of the illuminant represents the chromaticity coordinates for all achromatic objects from black to white. This is called the white point.

Thus the point on the chromaticity diagram having the coordinates of the illuminant represents the point of achromatic colours and around this point are arranged the various hues as shown in the Fig. (4.4). The contours of the constant hue are shown for the condition of standard day light illumination. These are derived by measuring under day light the tristimulus values of light reflecting from colour samples of the Munsell colour atlas. As the distance from the white point varies, saturation of colour increases and varies from achromatic at the white point to maximum saturation at the spectral locus. The concept of 'applied colour theory' can be associated with particular regions of chromaticity diagram at least approximately with particular sensations. The colours perceived in colour photography and colour television etc. can be predicted with reasonable accuracy by 'applied colour theory'.

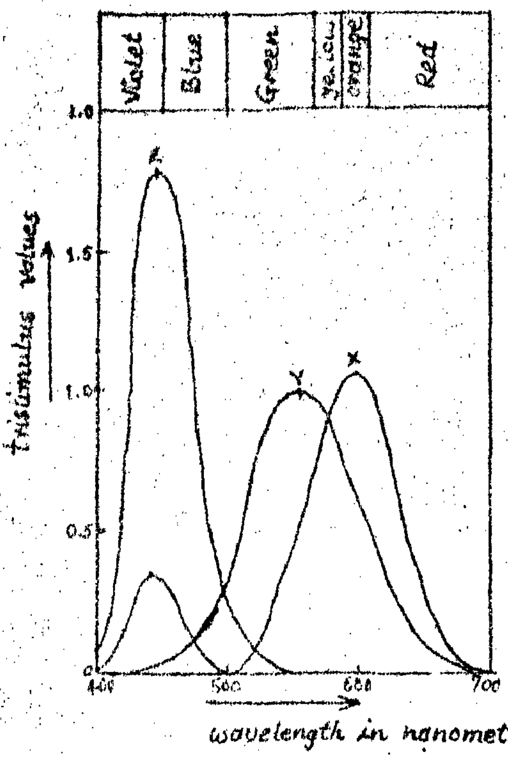


FIG 4.1 Colour mixing weighting functions of standard observer defined by CIE

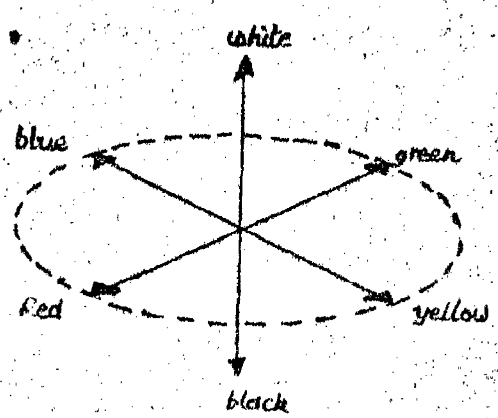


FIG-4.2 Coordinates of Colour-perception proposed by Hering

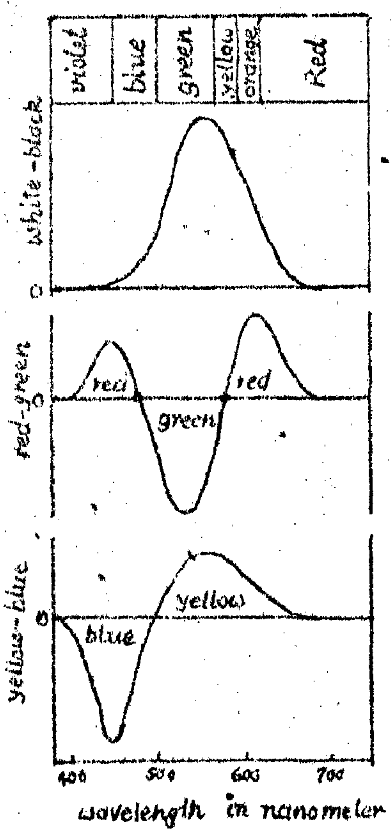


FIG-4.3 Spectral responses of Hering opponent-colour signals

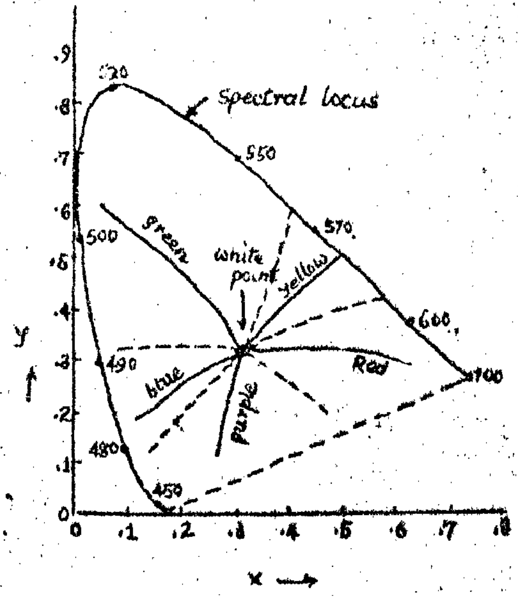


Fig-4.4 Chromaticity diagram

Land's two colour projection proved that 'applied colour theory' does not really work. It fails to predict the colours in a two colour projection and it fails grossly. It is not just that the colours are different from what the theory predicts but rather they are different in a unique way. So Land's fundamental contribution was to prove that present colour vision theory fails severely in predicting colours perceived in complex situations. So a more effective model of colour vision' Land's Retinex model' was proposed. Actually it is an extension of Adam's model which includes effects of 'simultaneous adaptation' to the successive adaptation considered by Adams.

In his retinex model Land proposes that retina has three type of cones with different spectral responses and that the signals from all the cones of each type modify one another in a neurological network, called retinex. The resultant modified neurological signal is equivalent to a scale of lightness. These lightness signals in the three retinex channels are compared to form the colour sensation.

The physiological problem faced by Land's retinex model is that the 'retinex' neurological network was not observed in electron microscope studies but Land clarified it by suggesting that this comparison of the receptor signals in each retinex may be perfommed in the brain. But following this we reach the conclusion that Herings opponent colour signals be generated in the brain because they must be formed after retinex comparison. A possible hypothesis that could remove this contradiction is the assumption that the colour information is time shared in retina by which single retinal neurological network performs spatial integration functions of the three separate retinex networks.

Time Sharing Models of Colour Vision

In time sharing models, different colour signals are transmitted independently along a single nerve fiber so a single neuron conveys full colour information and then retina compares the colour signals from different points in the visual field without requiring separate neurological circuits for different colour signals. In 1922 Troland postulated a time sharing model of colour vision. A postulation of 'modulation' model, in which average value of the neural signal conveys the achromatic information and modulations on the neural signal convey red-green and yellow-blue colour information. Average frequency of the nerve impulses in nerve fiber represents achromatic information and frequency modulation carries chromatic information when the eye is stimulated by fickering black and white patterns between 2 and 10 cps faint but very definite colour sensations can be evoked, called Fechner colours. Fry studied Fechner colours extensively and modified the Troland's model by proposing a set of modulation set for red, green, yellow and blue sensations. Schroeder proposed a model of colour discrimination based on optical wave interference within a single cone. The postulated that full colour data is fed out of the cone in accordance with Troland's model.

Biernson postulated that retinal cones sense nearly full spectrum of received light and retina uses this full spectral data' to perform successive and simultaneous adaptation. These colour data are time shared in order to avoid need of many parallel neural networks consistent with retinal anatomy: As postulated, each cone employs a scanning provess to sense the mode pattern in its outer segment. As the mode pattern varies in a complex manner with wavelength, it can provide much more spectral information than can a three colour system. The scan starts at the circumference of the outer segment and propagates inward to the axis. The scan activates only photopigment molecules at a particular radius at any instant. The scan in all the cones is synchronized and operate at a rate of 18-20 scans/sec. The effect of scan is to modulate the cone signal with the shape of the radial variation of mode pattern.

Hering opponent colour signals are extracted from the modulated waveform at the bipolar cells. Average value of the signal indicates white-black information, the red-green signal is approximately equal to the first derivative and the blue-yellow signal is approximately equal to the second derivative of the waveform.

Actually the waveform obtained by Fry in his model are identical to the waveforms derived from scanning process, as shown by Biernson and Synder. Both have shown that the colour signals for this model would have spectral responses qualitatively consistent with those of human colour vision. Successive and simultaneous adaptation is performed within the receptor cell layer in terms of mode pattern information, before that information is demodulated to fomm the opponent colour signals.

Colour Vision through Spectral Scanning[6]

The eye, in peceiving colour performs a wavelength discrimination, process which is analogous to the angular discrimination performed by radar. There are two basic principles for angular discrimination - (1) multiple detectors with different angular response characteristics, and (2) single detector which scans its response characteristic. This method of colour perception deals with the second approach using single detector unlike previously postulated methods of colour perception using multiple detectors. A wavelength dependent effect within the cone causes light of different wavelengths to produce different spatial distributions of energy in the photodetector region. An electrical process scans across this photodetector region producing a modulated waveform which defines the colour informations. The dc value of the waveform gives the white information, the first harmonic gives the blue-yellow information and second harmonic gives the green-red information. The phase determines difference between blue and yellow and between green and red. The waveform is demodulated in the retina to generate separate dc voltages which produce white-black, blue-yellow and green-red sensations.

Almost every theory, pertaining to colour perception, universally, followed the three different types of photo-sensitive receptors, postulated by Thomas Young. The primary effort of colour vision theory relies on three or more spectral sensitivity curves of colour vision but regardless of what curves are assumed or what processing is assumed for the signals derived from those curves, colour vision theories continue to run into serious contradictions. This theory is quite different from Young's principle.

Principle of Angular Scan

In colour vision the eye performs a wavelength discrimination function which is analogous to the other discrimination functions ~~of~~ performed by electronic systems as in radar systems while tracking a target. Fig. (4.5) shows the two principles of angular scan (1) by the use of multiple radar detectors having different angular response characteristics (2) by the use of a single detector which varies or scans its angular response characteristic. Fig. (4.5a) shows a multiple detector approach. Detector A (which may consist of a waveguide horn feeding a crystal detector) is pointed along the upper dashed line and therefore has a peak response in that direction, while detector B points along lower dashed line. Along the solid horizontal axis, bisecting the angle of dashed lines, both detectors have equal responses. To generate the colour discrimination signal the signal from detector B is subtracted from signal from detector A. This subtraction signal or resultant angular discrimination signal i.e. error signal is zero for a target along the horizontal axis (called the boresight), positive for targets above the axis and negative below the axis. Following this target T_1 gives positive error signal and T_2 negative error signal. For targets reasonably close to the boresight the error signal is approximately proportional to the angular deviation (or error) of the target from the boresight.

Fig. (4.5b) illustrates angular scanning approach. A single detector is oscillated through an arc, such that its direction of maximum sensitivity varies with time between the two dashed curves. The effect of this scanning is to produce an amplitude modulation of the signal delivered by the detector. We are interested in the first harmonic of that modulation which is at the frequency of angular oscillation of the detector. For a target along the boresight, first harmonic is zero. For a target above the boresight (T_1) the first harmonic has positive phase relative to the detector oscillation, whereas for a target below the boresight such as T_2, the first harmonic has negative phase. The first harmonic has maximum amplitude if the target lies along one of the dashed curves and in the viscinity of the boresight the amplitude of the first harmonic is proportional to angular deviation of the target from the boresight. The first harmonic is demodulated by phase sensitive demodulator from amplified detector signal using detector oscillation signal as reference. The demodulator delivers dc signal essentially equivalent to that which is delivered by multiple detector system.

The difference between two approaches is that multiple detector system is very difficult to keep in calibration because it requires two parallel amplifier channels the gains of which must be kept matched. The scanning-detector system is much simpler to build but has the disadvantage that inaccuracies are produced if the signal from the target is modulated at a frequency close to the angular scan frequency.

The angular scan system can be deceived by a jammer which modulates its return signal. Fig. (4.6) shows how the angular oscillation or scanning of detector modulates the detector signal.

Fig. [4.6(a)] shows the angular response pattern of the detector when it is at the extreme points in the oscillation cycle. The oscillation of the detector vibrates the pattern between the two curves. The angular positions of the targets T_1 and T_2 are shown. It is seen that as the pattern vibrates back and forth the signals produced by radar returns from targets T_1 and T_2 are modulated with opposite phase, i.e. while the signal due to target T_1 is increasing, that due to target T_2 is decreasing. Fig. [4.6(b)] shows the amplitude of the first harmonic of the ac signal as a function of angular deviation of the target from the boresight. The different signs indicate opposite phase of Ac component.

Fig. [4.6(c)] shows the detector signals produced by radar returns from targets T_1 and T_2. They have ac modulations about an average dc value and are opposite in phase if both targets were present simultaneously and produced radar returns of equal strength, the ac components would cancel and average value could be doubled. This would give a false impression of target being along boresight. This problem is avoided in most radars by a range ~~gede~~ gate that accepts only a single target return at a time.

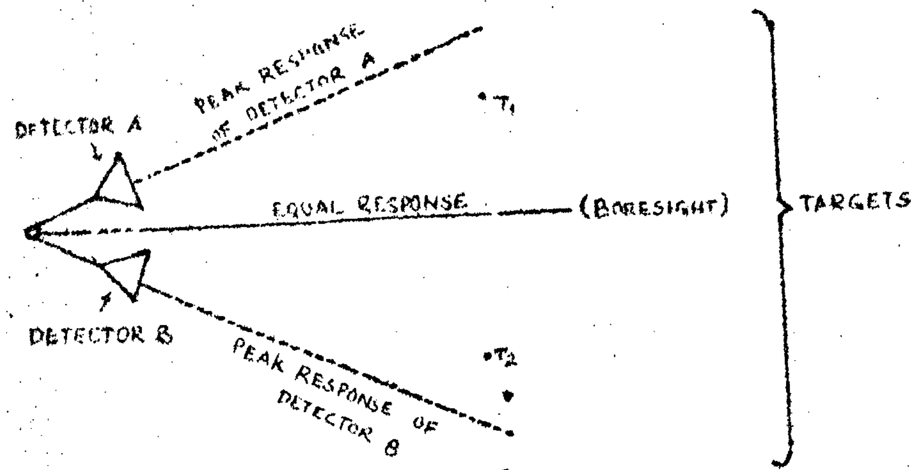


FIG (4.5) a

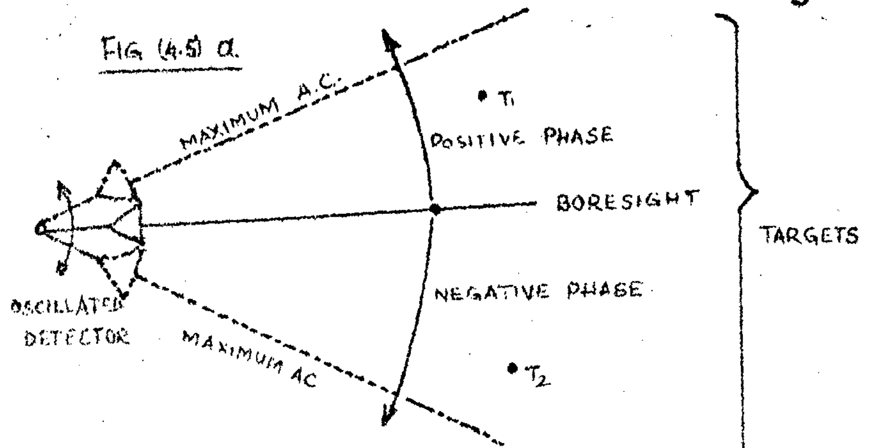
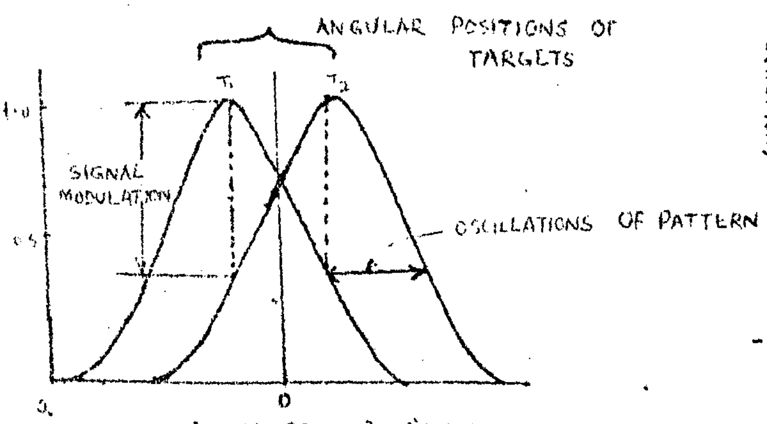
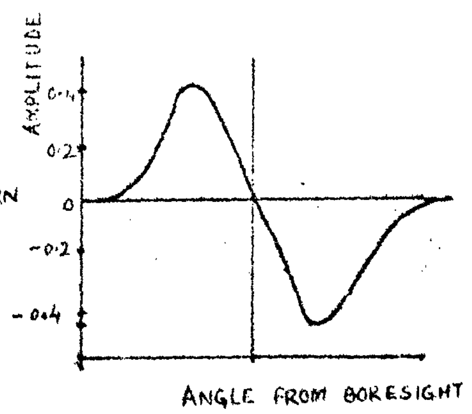


FIG (4.5) b

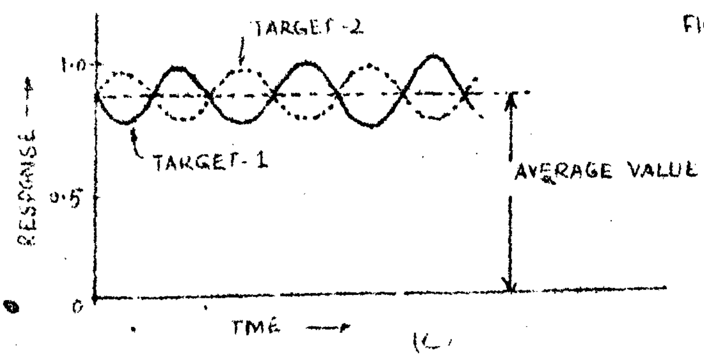
FIG-(4.5) TWO BASIC TECHNIQUES FOR ANGULAR DISCRIMINATION IN RADAR SYSTEMS (a) DISCRIMINATION WITH TWO DETECTORS (b) DISCRIMINATION WITH SINGLE OSCILLATED DETECTOR



(a)



(b)



(c)

FIG-(4.6) HOW OSCILLATION OF DETECTOR PRODUCES AC MODULATION OF DETECTOR SIGNAL (a) DETECTOR RESPONSE VS ANGLE AT EXTREME POINTS OF THE OSCILLATION CYCLE (b) AMPLITUDE OF FIRST HARMONIC OF MODULATION (C) RESPONSE OF DETECTOR VS TIME FOR TARGET T1 AND T_2

Scanning Principle in Colour Vision

Assuming that the detector oscillates its spectral response in the same manner as in angular scan, a monochromatic light would produce an ac modulated waveform just as a single target with angular scan does. A white spectrum of light would correspond to an infinite number of targets. The components due to various wavelengths would cancel and a dc signal delivered by the detector would correspond to white sensation and the ac component would correspond to chromatic sensation.

There are two sets of basic chromatic sensations experienced in vision yellow-blue and green-red, blue acting as a negative of yellow and green acting as a negative of red. This suggests that there are two different ac modulation components in colour vision, one component corresponding to yellow-blue and the other to green-red. The phase of a component would determine the difference between blue and yellow or between green and red. The two components could be kept separate by being at different frequencies or by being 90° out of phase with respect to one another.

One of the problems associated with conventional radar angular scan is that the target echo must be present for a time longer than one cycle of scan in order for the angular discrimination to be performed. However, in analogous colour vision situation the eye is able to see colour from a very short pulse of light, much shorter than any reasonable scan period. How then can the scanning principle be applied if this condition must be satisfied? It is accomodated by assuming that the scanning process in colour vision is performed subsequent to detection rather than prior to detection, as in angular scan.

A prismatic effect within the cone separates the wavelengths of incident light, such that different wavelengths are concentrated at different regions of the photodetector portion of the cone and excite, the photopigments and generate electric charges. The scanning mechanism scans back and forth across the detector and feeds out the charges from different portions of the detector at different instants of time.

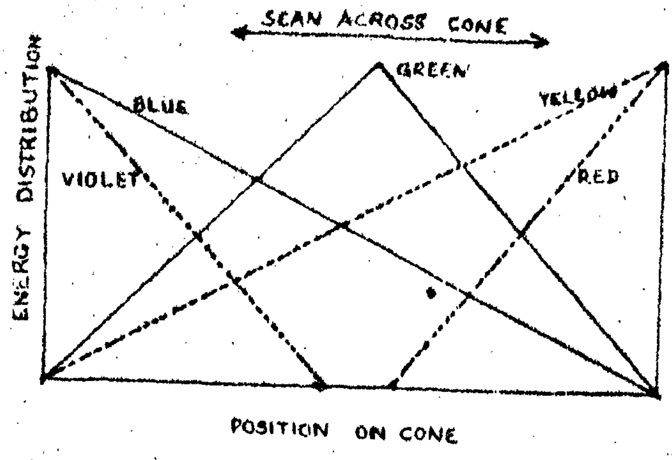
The prismatic effect does not separate the wavelengths discretely but produces different distributions of energy across the photodetector for different wavelengths. Dielectric waveguide patterns within the cone are probably responsible for prismatic effect. The scanning action could be produced by an oscillating electric field that controls the flow of charge from photodetector.

In order for the scanning to be performed in simplest manner the blue-yellow and green-red modulations should be harmonically related. Evidence suggests that the blue-yellow signal is a first harmonic and the green-red signal is a second harmonic Fig. (47a) shows a first approximation how the optical energy appears to be distributed across the photosensitive portion of the cone by prismatic effect. Energy distributions for specific wavelengths in the violet, blue, green, yellow and red portions of the spectrums are shown and are normalised to unity for convenience.

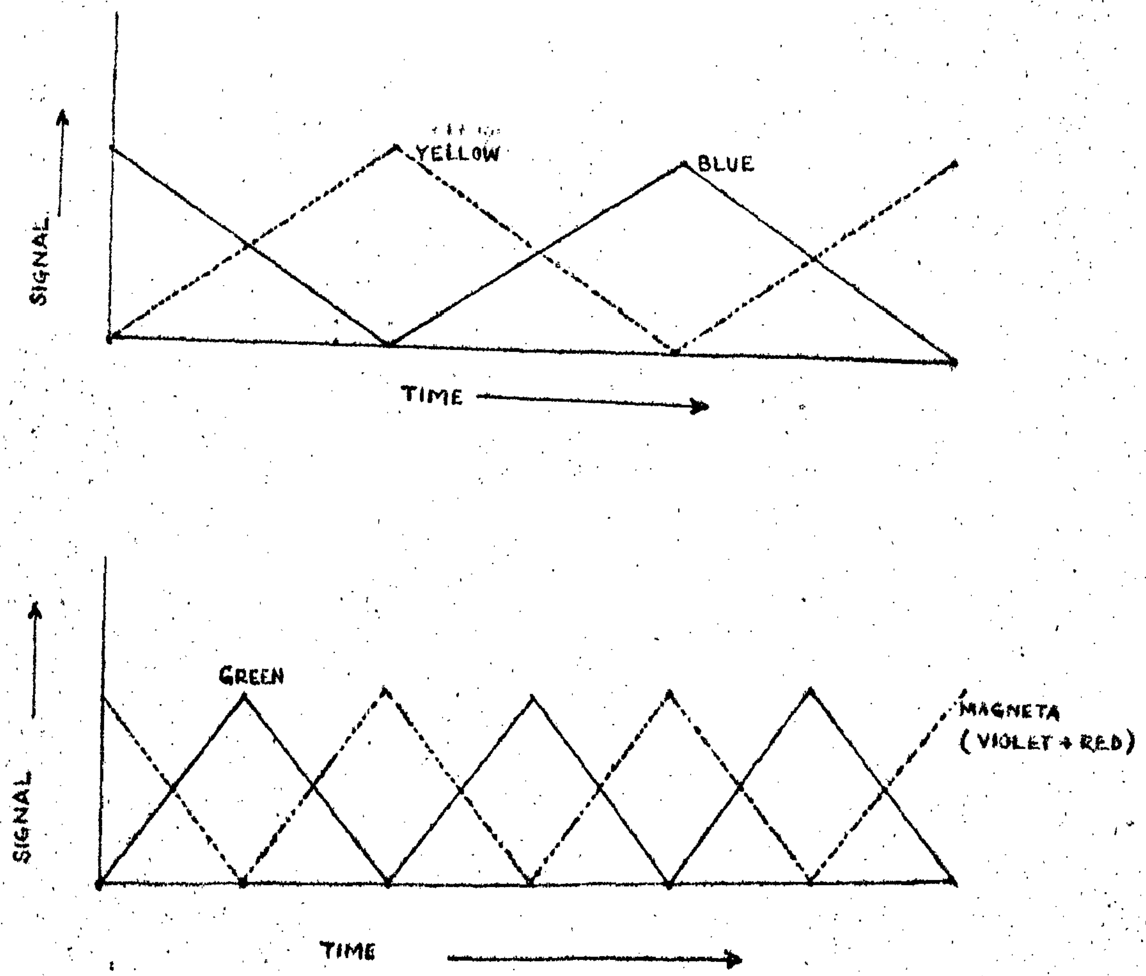
Electrical scanning mechanism scans back and forth across the photosensitive portion of a cone in a cyclic manner as indicated. The effect of this scanning is to produce the waveforms shown in Fig. (4.7b) for wavelengths corresponding to the energy distribution in Fig. (4.7a). The lower dashed portion of Fig. (4.7b) is produced by a mixture of two wavelengths red plus violet, combined to form a magneta colour sensation. Neglecting harmonics above second, the yellow and blue wavelengths generate first harmonics of opposite phase, while the magneta and green wavelengths generate second harmonics of opposite phase. For the particular wavelengths considered, blue, green, yellow and magneta, simple waveforms are produced. Intermediate wavelengths produce both first and second harmonics. Note that magneta (which is purple red i.e. red plus violet) is a natural primary in this theory, rather than red, even though magneta is not a spectral colour.

The waveforms are demodulated in the retina to form dc signals of opposing signs which produce the blue-yellow and green-magneta sensations. The waveforms are filtered to leave average value which gives the black-white or luminosity, sensation.

Fig. (4.8) gives a plot of the yellow-blue ac signal Vs. the green-'red' (or magneta) ac signal for spectral lights of equal energy. The numbers along the curve show the wavelengths in millimicrons. The shaded regions give the approximate colour sensations evoked by these wavelengths under



(a)



(b)

FIG-4.7 (a) ENERGY DISTRIBUTION ALONG PHOTOSENSITIVE PORTION OF THE CONE

(b) SIGNALS DELIVERED BY THE CONE FOR VARIOUS WAVELENGTHS OF LIGHT normal viewing conditions. The plot is calculated from standard colour mixture data plus a knowledge of the wave-lengths at which various types of colour blind individual experience a grey sensation.

A confusion group, why two oscillation modes are used in colour vision and a single oscillation mode is adequate for radar angular discrimination. The clarification is that radar performs angular discrimination on a single target whereas the receptor of the eye experiences many different wave-length regions simultaneously and requires an additional perceptual dimension to resolve wavelength mixtures. For example considering an ideal radar with linear response shown in Fig. (4.9a) The errors signal is +1 when target is at angle θ, zero when at θ_2 and -1 at θ_3. Thus radar can determine angles of the single target by error signals, But when two targets are simultaneously at θ_1 and θ_3 as the error signals are cancelled and we get zero error signal confusing to a single target at θ_2. To remove the ambiguity of multiple targets, an additional mode of scanning which generates the characteristic shown in Fig. (4.9b) is employed. If multiple detectors are employed a third detector can be used which subtracts its output from the sum of the other two. The targets at angles θ_1, θ_2 and θ_3 produce signals in the second mode B, corresponding to the points indicated by 1, 2, 3.

Signals from A and B modes when plotted on orthogonal axis simultaneously give a plot of Fig. (4.9c).

If the targets appear simultaneously, a means has been provided for defining, in an unambigonous sense, the general positions of ~~the~~ the targets, even though the radar can not breakdown the multiple target return into its separate components to determine the exact positions of the separate targets.

The dashed circle Fig. (4.9c) shows the analogous colour wheel and how the colour sensations are oriented around the wheel. By using two chromatic coordinate in colour tracking, the eye is able to distinguish a wavelength region at the center of the tracking zone (at point 2 in the yellow green) from the sense of two wavelength regions at the ends of the tracking zone (at point 1 in the red and point 3 in the blue) which combine to produce point 4 in the purple).

Thus two chromatic coordinates are required for the eye to distuingish among the various spectral regions in an unambiguous manner. For this reason the eye requires two scanning modes for colour discrimination, whereas a radar tracking system needs only one.

When white light is modulated at frequencies in the range of 10 cps to 20 cps chromatic sensations are produced which are called Fechner colours. The frequency at which Fechner colours are observed increases with light intensity which appears to indicate that the eye increases its scan rate with increasing light intensity.

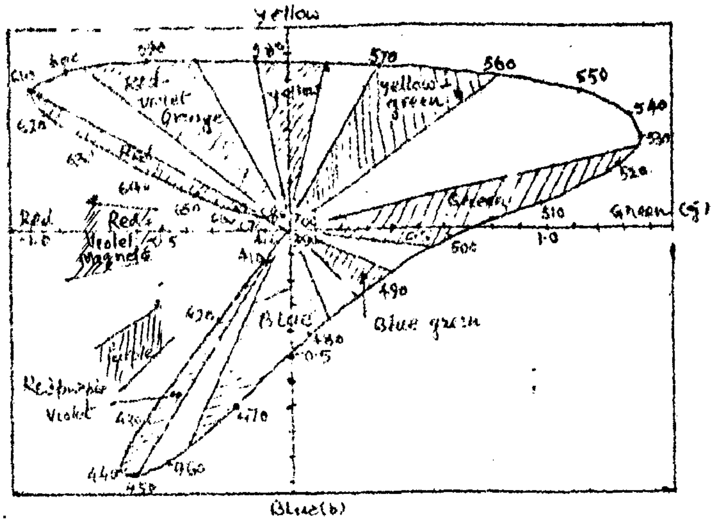
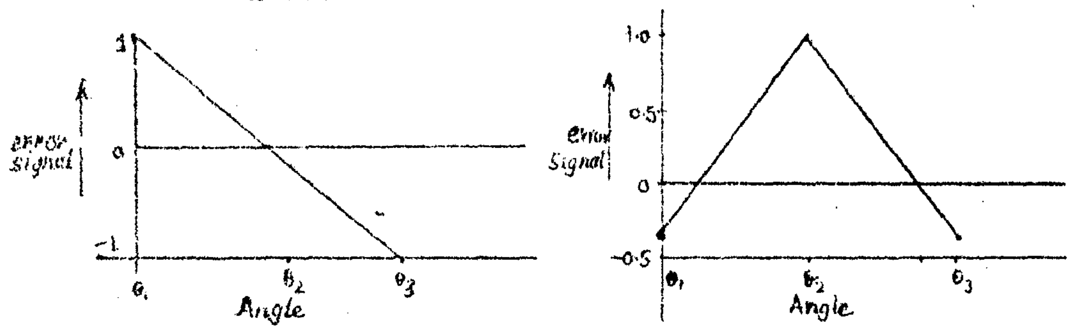
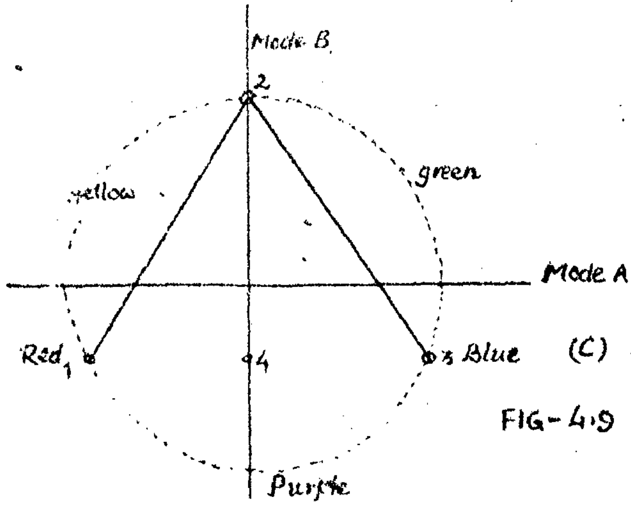


FIG - 4.8 Plot of yellow-blue ac components Vs. green-red ac component for equal energy spectral lights with wavelength in millimicrons as a variable



(a) Error signal from mode A (b) Error signal from mode B.



(C) Plot of signal from mode A Vs signal from mode B

FIG - 4.9

CHAPTER - 5

PROCESSING AND RECOGNITION OF SIMPLE PATTERNS [7],[8],[16]

In this chapter, we have dealt with some simple methods for extracting the features of uncomplicated patterns and recognition thereby. These procedures may be the representative of the processing and recognition of simple patterns in human brain, as human brain identifies the simple patterns without much effort. So, naturally, the process of recognition of such patterns should not be much complex. Three methods are discussed here:

A. Visual Feature Extraction by Multilayered Network [7],[21]

This feature extraction network system is composed of analog threshold elements which are equivalent to neurons in the retina and visual cortex. Each analog threshold element receives inputs from a large number of elements in the neighbouring layers and performs its own special functions. It takes care of one restricted part of the photoreceptor layer on which an input pattern is presented and it responds to one particular feature of the input pattern such as brightness contrast, a dot in the pattern, a line segment of a particular orientation or an end of the line. Therefore, the network performs parallel processing of the information. With the propagation of the information through the layered network, the input pattern is successively decomposed into dots, groups of line segments of same orientation and the end of these lines.

Although we know little about the information processing in human brain, but we can partly deduce it from the literature of neurophysiology and psychology and can try a multilayered network for feature extraction of a given pattern. The presented system for feature extraction has been designed with full regard to mechanisms of visual systems. An effort has been made to incorporate the mechanisms of biological systems into the network. An engineering approach to this network analyzes first what visual features should be extracted and then a network ~~a~~ is designed to extract those features effectively.

As a neuron is excited, it yields a pulse train at output and the information is carried in the form of pulse density modulation. The information processing in the neuron network is mainly done at synapses, if a neuron fires its output is transmitted to the next neuron through synaptic connection. The inputs to the neuron may be excitatory - the strong input at which increases pulse density at output and inhibitory - the strong input at which decreases pulse density. The number of synaptic connections to a single neuron may vary from hundreds to thousands in case of neurons in the visual cortex.

The information flow path in the visual system follows from ~~low~~ Lens to mosaic of receptor cells in retina, from bipolar cell to retinal ganglian cells, from ganglian cells to optic nerve and then to lateral geniculate bodies, The output from lateral geniculate bodies is transmitted to the area 17, in the cerebral cortex, then to area 18 and then to area 19. Retinal ganglion cell or lateral geniculate cell shows a response as shown in Fig. (5.1a or b) The response of the cell is intensified or respectively. Thus receptive fields may be on-center field (Fig.5.1a) and off center field fig(5.1b). Receptive fields of the cells in area 17 of the cerebral cortex are quite different from those of the lateral geniculate cells and receptive fields as shown in Fig. (5.1c&d) are found plentifully. The neurons which have these receptive fields are called simple cells and respond strongly to line (or edge) stimuli provided the position and orientation of the line are suitable for particular cell 'Complex cells' respond to line stimuli but the position of the line is not critical and the cell continues to respond even if properly oriented stimuli are moved as long as they remain in the cells receptive field. These cells are found in area 18 but also in area 17.

Hypercomplex cells: These are found in area 18 and 19. These neurons respond to complicated combinations of features of input patterns. For example one of them responds to the corner of the figure projected on the retina and another one responds to line stimuli of a particular orientation but only when the line strength is in a particular range specific to the cell.

Synthesis of feature extracting network. Analog threshold element

Analog threshold element is functionally analogous to the neuron. The output of an element is an analog valve positive or zero, which corresponds to the firing of the neuron. Every input to the neuron, through synaptic connection, has its own interconnecting coefficient, positive or negative, for excitatory or inhibitory synapse respectively. The output of the element is linearly proportional to the sum of input signals taking into consideration its interconnection coefficient, provided the net input is more than threshold, (which is set zero). When net sum is zero ~~of~~ or negative, output is zero. Mathematically $v = \varphi\left\{\sum_{i=1}^{k} c(i)u(i)\right\}$ -(1) where v = output, c(i) = interconnection coefficient of input u(i), i = 1 .. k and $\varphi(u)$ describes the nonlinear transfer characteristic of element, namely

$$\varphi(u) = \begin{cases} u & u \geq 0 \\ 0 & u < 0 \end{cases} \qquad (2) \quad \text{Fig. } (5.2)$$

$\varphi(u)$ has been selected nonlinear to introduce in the multilayered network the superior ability than two layered network because if a multilayered network consists of only linear elements, the response of an arbitrary element in the network can be described simply as a linear sum of the outputs of first layer to which pattern is presented i.e. photoreceptor layer. It exploits then full capability of multilayered network.

<u>Network</u> [11]

Multilayered network of elements is used for the processing of motionless line drawn patterns. The network mainly extracts dots and straight lines from the pattern (it has no curve detector). First of the seven layers of the network shown in Fig. (5.3), is an array of photoreceptors on which an input pattern is optically projected. Rest layers consists of threshold elements and each threshold element receives its input from neighbouring layers but elements in the same layer do have no interconnection. The arrangement of elements and their interconnections are all homogeneous over a given layer

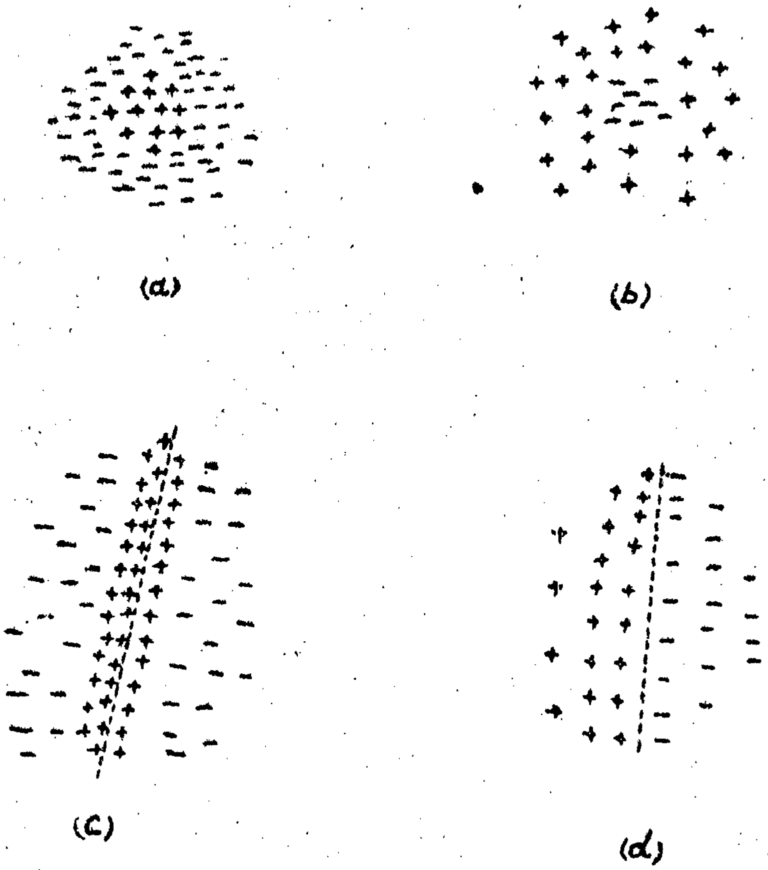


FIG - 5.1. (a) ON-CENTRE GENICULATE RECEPTIVE FIELD
(b) OFF-CENTRE GENICULATE RECEPTIVE FIELD
(c), (d) COMMON ARRANGEMENTS OF SIMPLE CORTICAL RECEPTIVE FIELDS

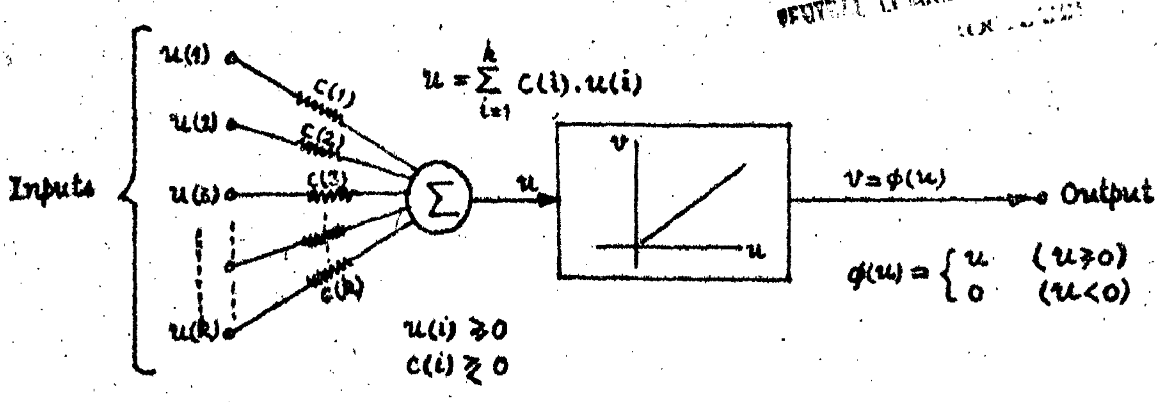
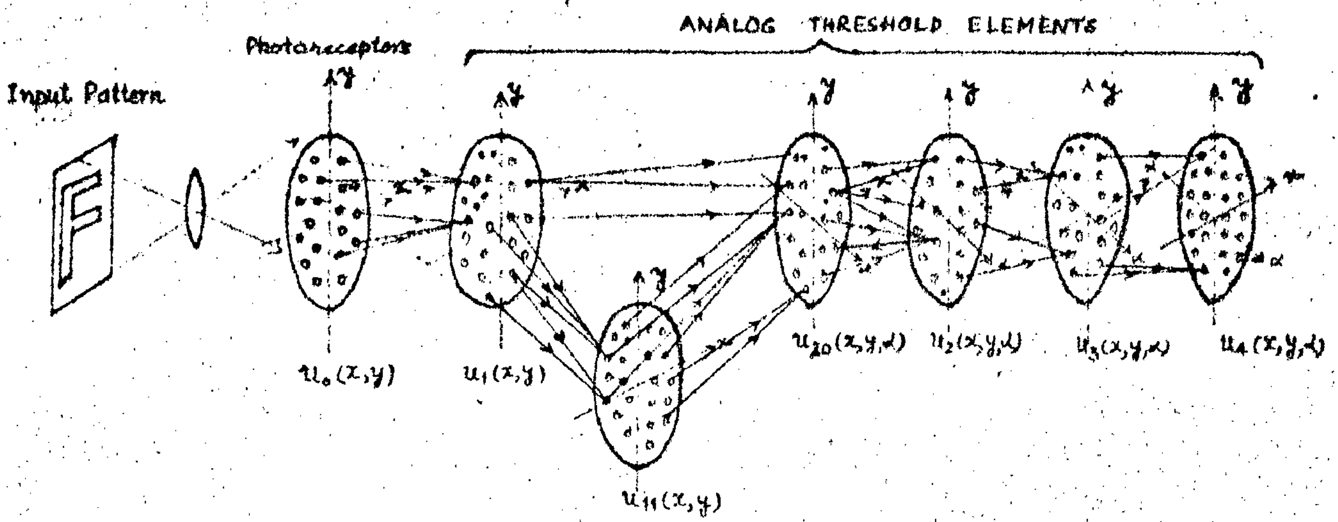
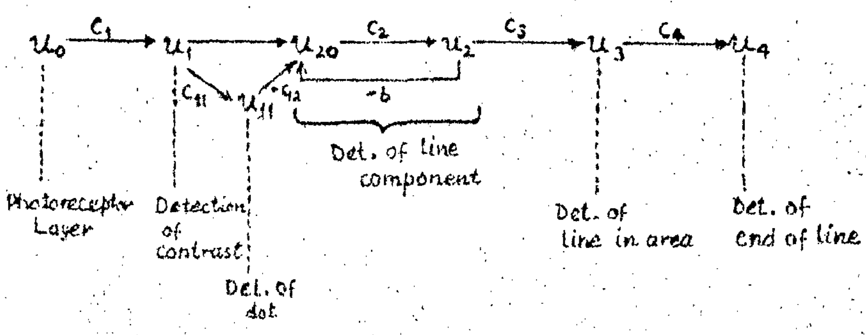
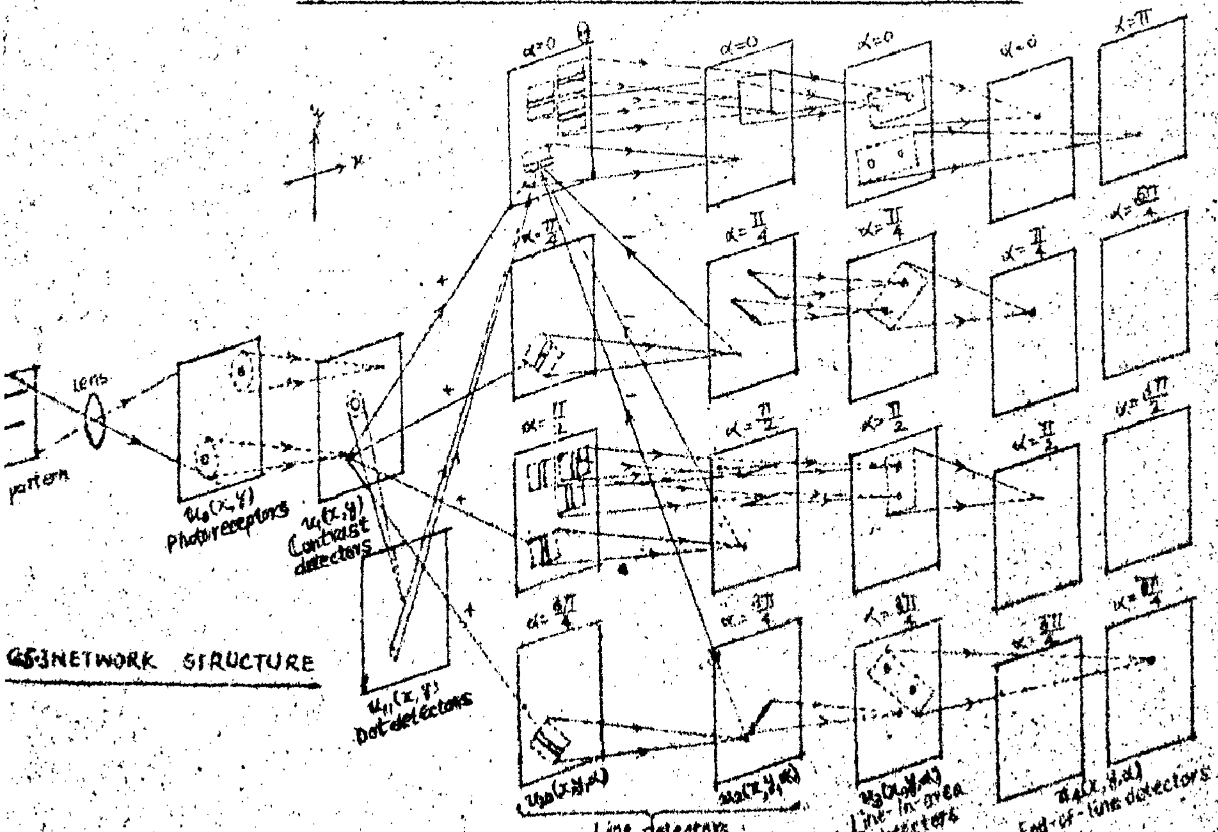


FIG - 5.2 ANALOG THRESOLD ELEMENT





Symbols used to represent layers and their connections



G5.3 NETWORK STRUCTURE

and all elements of one layer have same set of interconnecting coefficient. The information through parallel processin is transmitted fron one layer to the other through interconnections. In different layers the pattern is gradually decomposed into dots, groups of line segments of same orientation, the ends of line segments and so on.

Photoreceptor Layer (U_o)

It is a two dimensional array of photoreceptors with no interactions among themselves. As pattern is projected on this layer the output of the elements depending on the light incident upton it produces positive output following a transfer characteristic linear or logarithmic. In cartesian coordinates $u_o(x,y)$ denotes the output of the photoreceptor situated at (x,y) point w.r. to certain x and y axis.

Detection of Contrast (u_1)

This layer has elements with on-center-type receptive fields as retinal ganglion or lateral geniculate cells. They detect brightness contrast in the input pattern and receive input signals from layer u_o. $u_1(x,y)$ denotes output of any element in this layer with position (x,y) in cartesian coordinates. $C_1(\xi,\eta)$ denotesinterconnecting coefficient of a u_1 element where ξ and η are the arguments to designate an individual input terminal. S_1 is the set of all points (ξ,η) of a single element for which $C_1(\xi,\eta) = 0$ holds.

$$u_1(x,y) = \varphi\left\{\iint_{S_1} C_1(\xi,\eta)\; u_o(x+\xi,y+\eta)d\xi\; d\eta\right\} \qquad (3)$$

$\varphi(u)$ describes nonlinear characteristic of the element: we have adopted only on-center type elements as to process an input pattern which is drawn with white lines on a black background. Otherwise we will select off-center-type elements if black lines are on white backgroung and $C_1(\xi,\eta)$ will change sign. Shape of $C_1(\xi,\eta)$ is shown in the Fig. (5.4). $C_1(\xi,\eta)$ satisfies the inequality $\iint_{S_1} C_1(\xi,\eta)\, d\xi\, d\eta = 0$ (4)

i.e. sum of positive and negative coefficients cancel each other. So integral in (3) eleminates the low frequency component of spatial frequency from $u_0(x,y)$. The diameter of the central on-area of receptive field determines the resolution of this feature extractor, too small an area is not desirable as it exaggerates the high frequency noise in the input pattern. It is proper to choose this diameter approximately equal to the width of the lines to be extracted. For a pattern with lines of various widths, it is preferable to choose the diameter approx. equal to the width of finest line. The diameter of the peripheral off area should be large compared to the width of widest line and preferably larger than the size of the letters to be processed.

<u>Detection of Dots</u> (u_{11})

Layer u_{11} extracts dots in the input pattern, having received the input signals from layer u_1. Output u_{11} is expressed as

$$u_{11}(x,y) = \varphi\left\{ \iint_{S_{11}} C_{11}(\xi,\eta)\, u_1(x+\xi,y+\eta)\, d\xi\, d\eta \right\} \qquad (5)$$

Interconnection coefficients are shown in Fig. (5.5). The shape of $C_{11}(\xi, \eta)$ resembles with $C_1(\xi, \eta)$ elements which have on-center type receptive field. The inhibitory surround of $C_{11}(\xi, \eta)$ however, is stronger in density and smaller in diameter than that of $C_1(\xi, \eta)$. The interconnecting coefficients $C_{11}(\xi, \eta)$ have been determined in such a way that the element $u_{11}(x,y)$ will respond to a dot pattern situated at a pattern relative to the receptive field Fig. (5.6a,b) but not the patterns as in Fig. (5.6c,d). The diameter of the central area of the receptive field is chosen approximately of the size of the dots in the pattern. The width of inhibitory surround should be determined according to the distance between a dot and other components of input pattern.

<u>Detection of Line Components</u> (u_{20} and u_2)

u_{20} and u_2 layers detect line components of the pattern with final output from u_2. Elements in both these layers are arranged in three dimensional arrays. The element $u_2(x,y,\alpha)$ will respond to a line which passes through the point (x,y) of the photoreceptor layer and has an orientation $\alpha (0 \leq \alpha < \pi)$

Outputs of layers u_{20} and u_2 are

$$u_{20}(x,y,\alpha) = \varphi \Big\{ u_1(x,y) - \iint_{S_{12}} C_{12}\,\phi\,(\xi,\eta)\, u_{11}(x+\xi, y+\eta)\, d\xi\, d\eta - \int_{-\alpha}^{\pi-\alpha} b(\theta)\, u_2(x,y,\alpha+\theta)\, d\theta \Big\} \quad \ldots (6)$$

$$u_2(x,y,\alpha) = \varphi \Big\{ \iint_{S_2} C_2(\xi,\eta,\alpha)\, u_{20}(x+\xi, y+\eta, \alpha)\, d\xi\, d\eta \Big\} \quad (7)$$

The interconnecting coefficients $C_{12}(\xi, \eta)$, $C_2(\xi,\eta,\alpha)$ and b(θ) are shown in Fig. (5.7, 5.8), 5.9) There are backward interconnections as well as forward ones between layers u_{20} and u_2. i.e. there is a feedback loop between these layers. The elements in layer u_2 have receptive fields similar to those of simple cortical cells and respond strongly to line stimuli. The shape of the function $C_2(\xi,\eta,\alpha)$ is determined by the shape of the receptive field in simple cells. Layer u_{20} improves the ability of the network to extract straightlines but there is no physiological evidence of existence of such layer in visual cortex with backward connections.

If there were no u_{20} layer u_2 will directly receive its input from u_1 layer and $u_2(x,y,\alpha) = \varphi\left\{\iint_{S_2} C_2(\xi,\eta,\alpha)\, u_1(x+\xi\,, y+\eta)\, d\xi\, d\eta\right\}$ -(8) under this assumption receptive field of an element $u_2(x,y,\alpha)$, $\alpha = \pi/2$ is shown in Fig. (5.10a). This element responds to a vertical line presented to this element in position shown in Fig. (5.10b), but it does not respond to the lines shown in Fig. (5.10c to 5.10e) because the inhibitory inputs caused by the horizontal line suppress the excitatory input due to vertical line. The element also responds to an oblique line presented near the peripheral part of the receptive field shown in Fig. (5.10f). Fig. (5.10) shows an example of the response of the response of $u_2(x,y,\pi/2)$ in the case where u_{20} does not exist. So line components would not be faithfully extracted without layer u_{20}.

Fig. (5.11) shows how our system responds to a cross-shaped line with the help of u_{20} layer (only for particular

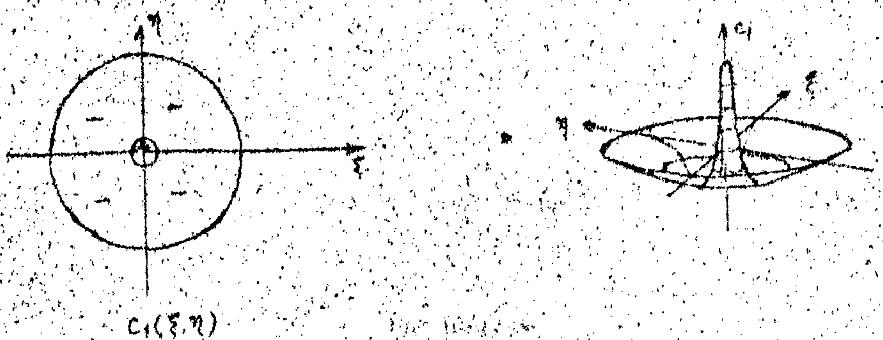


FIG- 5.4 (a) Plan view of the function $c_1(\xi,\eta)$ (b) Three-dimensional view of $c_1(\xi,\eta)$

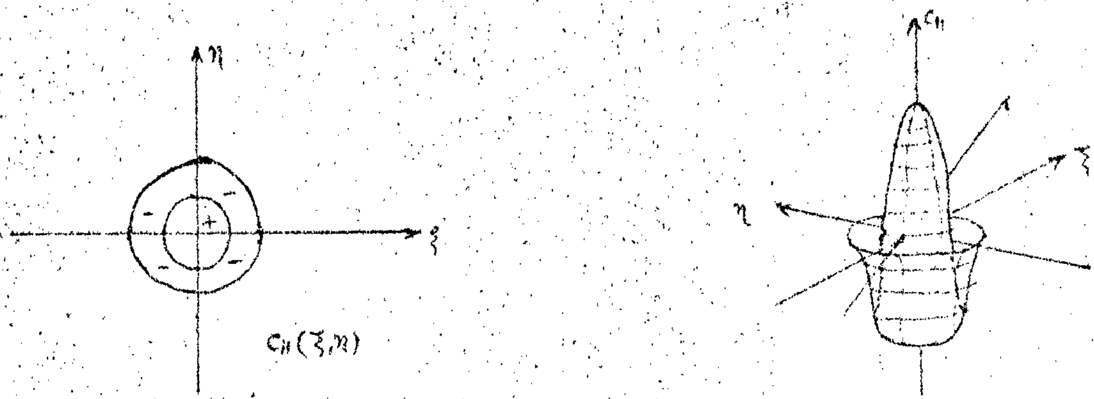
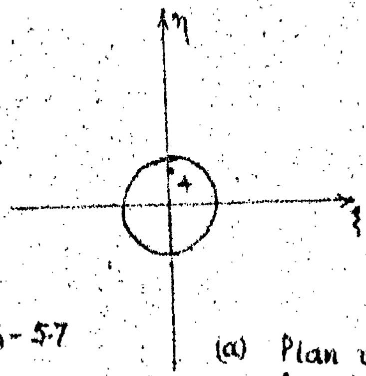


FIG- 5.5 (a) Plan view of the function $c_{11}(\xi,\eta)$ (b) Three-dimensional view of $c_{11}(\xi,\eta)$

FIG - 5.6 (a) (b) (c) (d)



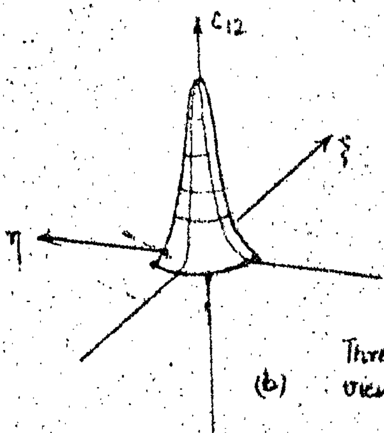


FIG- 5.7 (a) Plan view of the function $c_{12}(\xi,\eta)$ (b) Three-dimensional view of the function $c_{12}(\xi,\eta)$

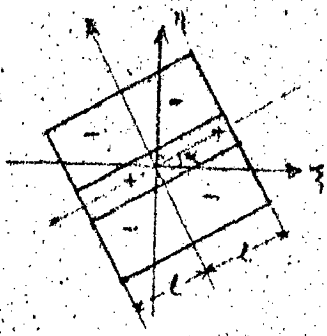
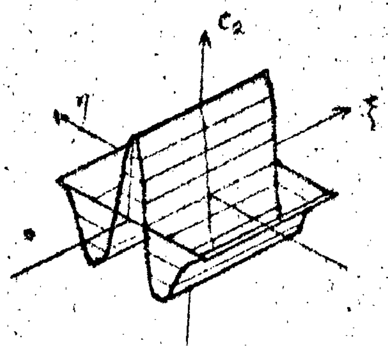


FIG-5·8(a) Plan view of the function $c_2(\xi, \eta, \alpha)$



(b) Three dimensional view of the function $c_2(\xi, \eta, 0)$

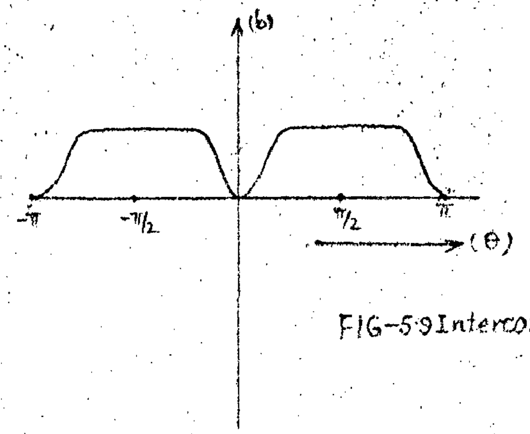


FIG-5·9 Interconnection of $b(\theta)$

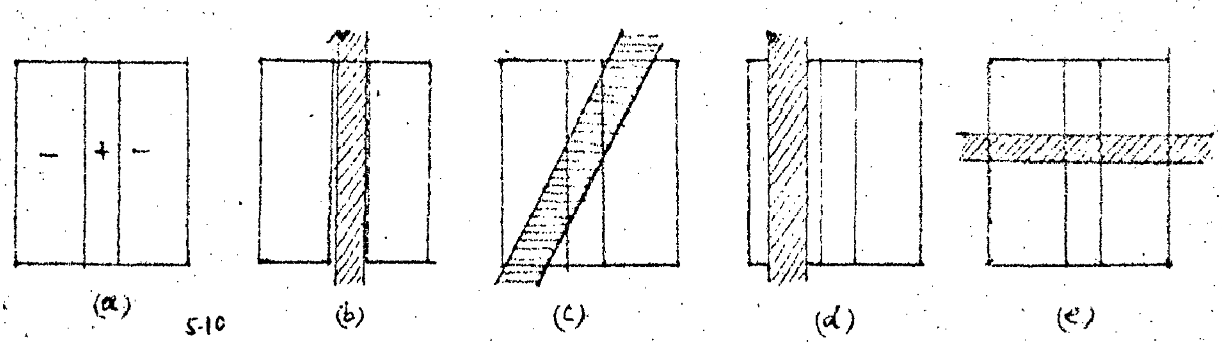


FIG-5·10 Response of $u_2(x,y,\alpha)$ (a) its receptive field. This element responds only to pattern (b) but not to patterns (c) to (e)

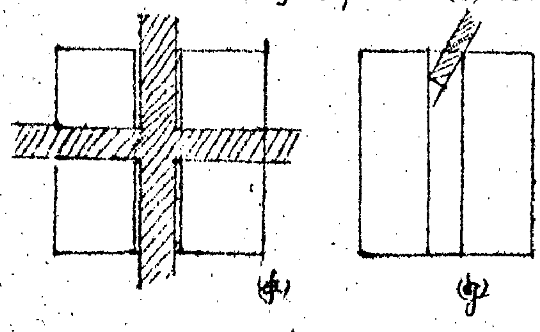


FIG-5·10 Patterns to which $u_2(x,y,\pi/2)$ would improvely respond if there were no u_{20} layer orientation of lines 0 and $\pi/2$) for simplicity). A horizontal line component is detected by $u_2(x,y,o)$ and a vertical line by $u_2(x,y,\pi/2)$. Horizontal line $u_2(x,y,o)$ inhibits the response of $u_{20}(x,y,\pi/2)$. At the same time a vertical line component is detected by $u_2(x,y,\pi/2)$ and this output inhibits the response of $u_{20}(x,y,o)$. After the response of this feedback loop reaches steady state, the outputs of $u_{20}(x,y,o)$ and $u_{20}(x,y,\pi/2)$ are shown in Fig. (5.11). So $u_2(x,y,o)$ and $u_2(x,y,\pi/2)$ respond to horizontal and vertical lines respectively without any interference from intersecting lines.

Layer u_{20} is also effective in suppressing the spurious ~~superious~~ response to an end of an oblique line and layer u_2 also does not produce spurious output as such a stimulus has already been suppressed in layer u_{20} by the feedback interconnection. In order to avoid this line-detecting circuit to avoid to respond for dot, stimuli from dots are inhibited by layer u_{20} by means of inhibitory connection $-C_{12}(\xi,\eta)$ from layer u_{11}.

This network can detect line stimuli even in case of blurring or mutilations of lines, or in dirty background. It can also accommodate slightly bend or jagged provided these distortions are small. The width and length of the excitatory (positive) area of the function $C_2(\xi,\eta,\alpha)$ is determined by considering conditions of distortions to be allowed and length of the shortest line in the pattern.

Detection of Line in Area (u_3)

This layer responds to a line with specified orientation irrespective of its position. An element continues to respond even if a properly oriented line is moved, as long as the line remains in the receptive field of the element. It gives more output when the line is near the centre of the receptive field. This layer corresponds to the complex cells in cerebral cortex. A given element in this layer is interconnected to the output of the element layer u_2.

$$u_3(x,y,\alpha) = \varphi\left\{\iint_{S_3} C_3(\xi,\eta,\alpha)\ u_2(x+\xi,y+\eta,\alpha)d\xi\ d\eta\right\} \quad \dots (9)$$

The shape of the function $C_3(\xi,\eta,\alpha)$ is shown in Fig. (5.12). For example, $u_3(x,y,\pi/2)$ receives excitatory inputs from many u_2 elements which have vertically oriented receptive fields, whose centers are situated along a horizontal line passing through the point (x,y). If any of the u_2 elements detects a vertical line it sends an excitatory input to the u_3 element and the u_3 element yields an output. The vertical length of the receptive field of u_3 element is the same as that of these u_2 elements. If the orientation of the line is not vertical, none of the u_2 elements will respond and so u_3 element also does not respond. So a given element $u_3(x,y,\alpha)$ detects a line component whose orientation is α without being much affected by the exact position of the line.

Detection of the End of the Line (u_4)

Element $u_4(x,y,\alpha)$ responds to an end of a line whose orientation is α. The range of variable α is $0 \leq \alpha < 2\pi$ for the u_4 elements, because we must distinguish an orientation of one end of the line from the orientation of the other end of the same line. These elements correspond to hypercomplex cell in visual cortex. Output of the element is

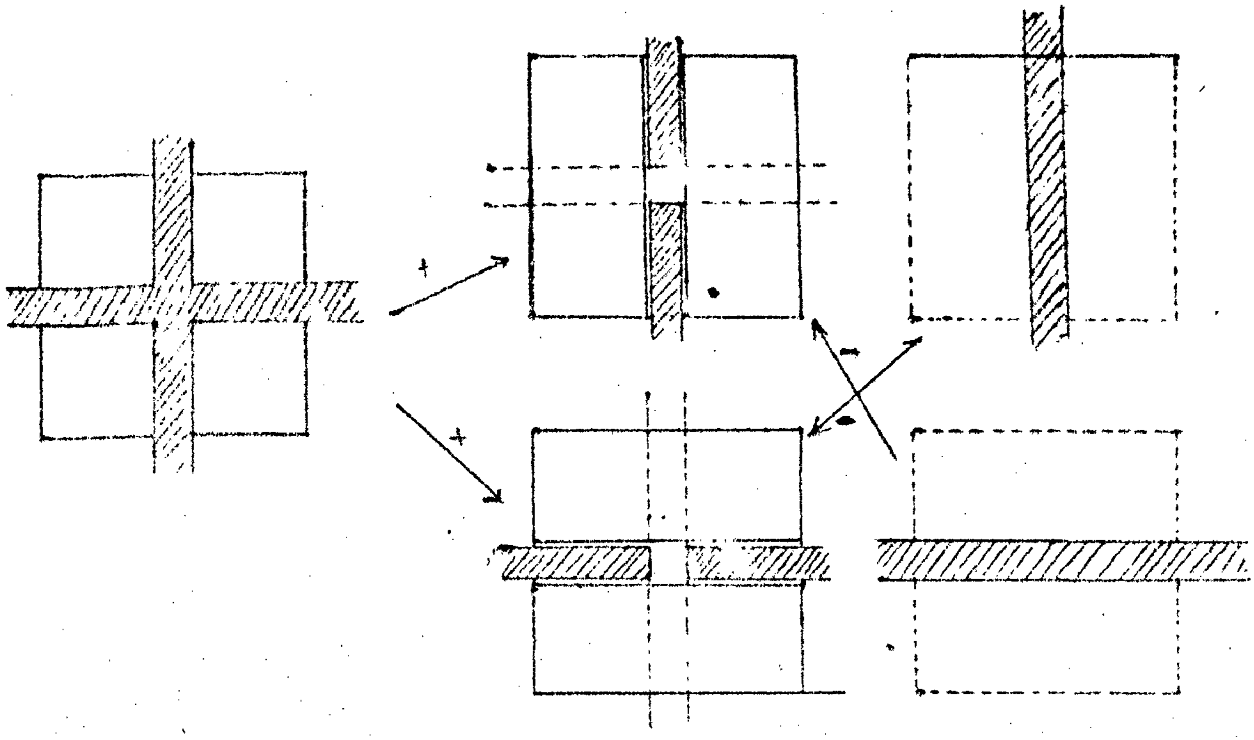


FIG-5.11 Illustration of the effect of u_{20} layer incorporating feedback

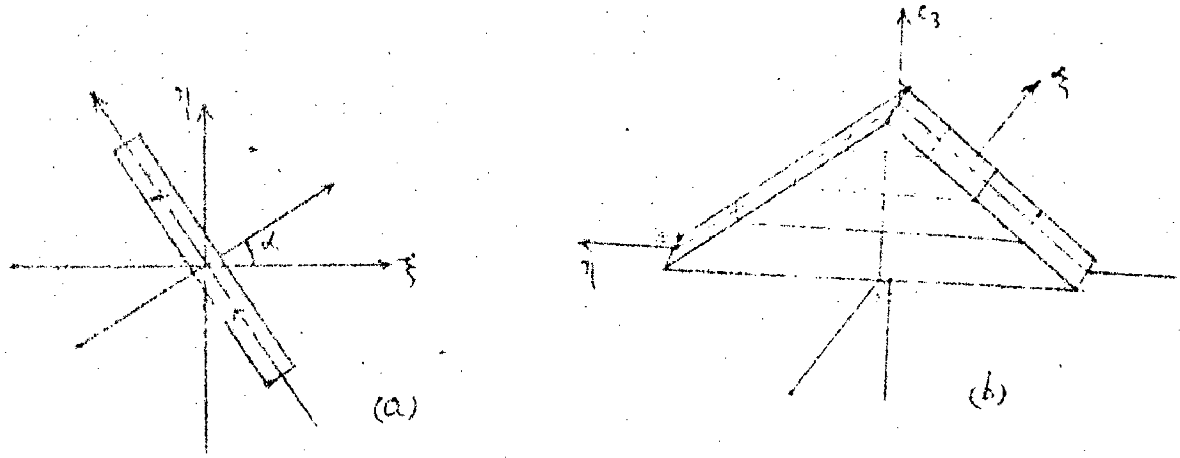


FIG-5.12 (a) Plan view of the function $c_3(\xi,\eta,\alpha)$ (b) Three-dimensional view of the function $c_3(\xi,\eta,0)$

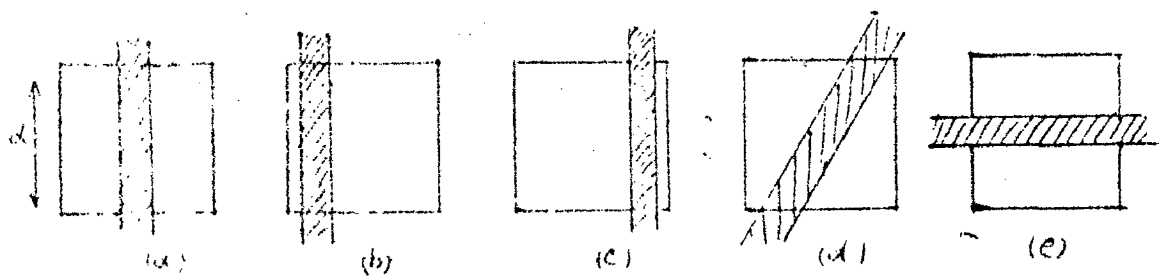


FIG. 5.13 Response of an element $u_3(x,y,\pi/2)$ for detection of line in area
It does not respond for (d) or (e) and produces less output for (b) or (c)
as line is located far from the centre

$$u_4(x,y,\alpha) = \varphi\left\{\iint_{S_4} C_4(\xi,\eta,\alpha)\cdot u_3(x+\xi,y+\eta)d\xi\, d\eta\right\} \quad (10)$$

~~Th~~

The shape of the function $C_4(\xi,\eta,\alpha)$ is shown in Fig. (5.14) which has positive pole at point ($l \cos \alpha$, $l \sin \alpha$) and negative pole at ($-l \cos \alpha$, $-l \sin \alpha$) and takes a slightly negative value in the domain outside these two-poles. Distance between the two poles is $2l$ which is the length of the receptive field of u_3, element. For simplicity's sake considering only interconnections of these two poles. Then output of u_4 element is

$$u_4(x,y,\alpha) \propto \left\{K_p \cdot u_3(x+l \cos\alpha, y+l \sin\alpha)\alpha) - Km \cdot u_3(x-l \cos\alpha,, y \cdot l \sin \alpha)\right\} \quad \ldots (11)$$

where $K_p = C_4$ ($l \cos \alpha$, $l \sin \alpha$, α) —(12) positive pole

$-K_n = C_4(-l \cos\alpha, -l \sin \alpha, \alpha)$ negative pole ... (13)

This u_4 element receives antagonistic inputs from two u_3 elements whose receptive fields adjoin each other in the direction of α, both of which respond to a line of orientation α (these two u_3 elements are called E and I respectively). The output of element E whose receptive field is shown with a olid line in Fig. (5.15a) is connected to element u_4 in an excitatory manner and an element whose receptive field is shown dotted is connected in an inhibitory manner when a stimulus like Fig. (5.15b,c) is presented element E is excited and I remains at rest for element u_4 is activated. If stimulus like Fig. (5.15d) is presented both elements E and I respond and cancel each other, so u_4 does not respond u_4 does not respond for input as in Fig. (5.15e) as it provides only inhibitory input. It does not respond to stimulus like Fig. (5.15f,g) as the orientation of the line is not α, neither E nor I is excited.

If there exists lack of symmetry in the width of line as shown in Fig. (5.15h) then even the middle of the line may, make the output of E more than I and seemingly, u_4 is excited. In order to avoid this delimma, $K_n > K_p$ is selected. If the line has a slight bend or lack of symmetry such that some part of E is excited and I gets no input, then element is excited. In order to avoid this the function $C_4(\xi, \eta, \alpha)$ has been made slightly negative in the domain outside the two poles as shown in Fig. (5.15i) and the element u_4 receives an inhibition proportional to the average activity level of u_3 elements near receptive field of u_4.

B. Feature Extraction by SLEN Concept [2], [12]

Assuming the macula portion of the eye, which performs visual pattern recognition, contain 34000 cones, equivally distributed for green, red and blue spectral maxima and discharge rates of adjacent cones are compared in neuron matrices, one third of 68000 , 22700 matrices are involved in comparison between identical colour pairs of cones. For geometric patterns all the information is supplied by these matrices for pattern recognition. The concept considered here, for pattern recognition is based on Hubel's findings.

Cells in the visual cortex are receptive to ON and OFF areas that are represented by light and dark dots, respectively. Features are selected by correlation i.e. short vertical lines are extracted by short vertical receptor arrays. We will assume that an idealized model consists of a short line of ON

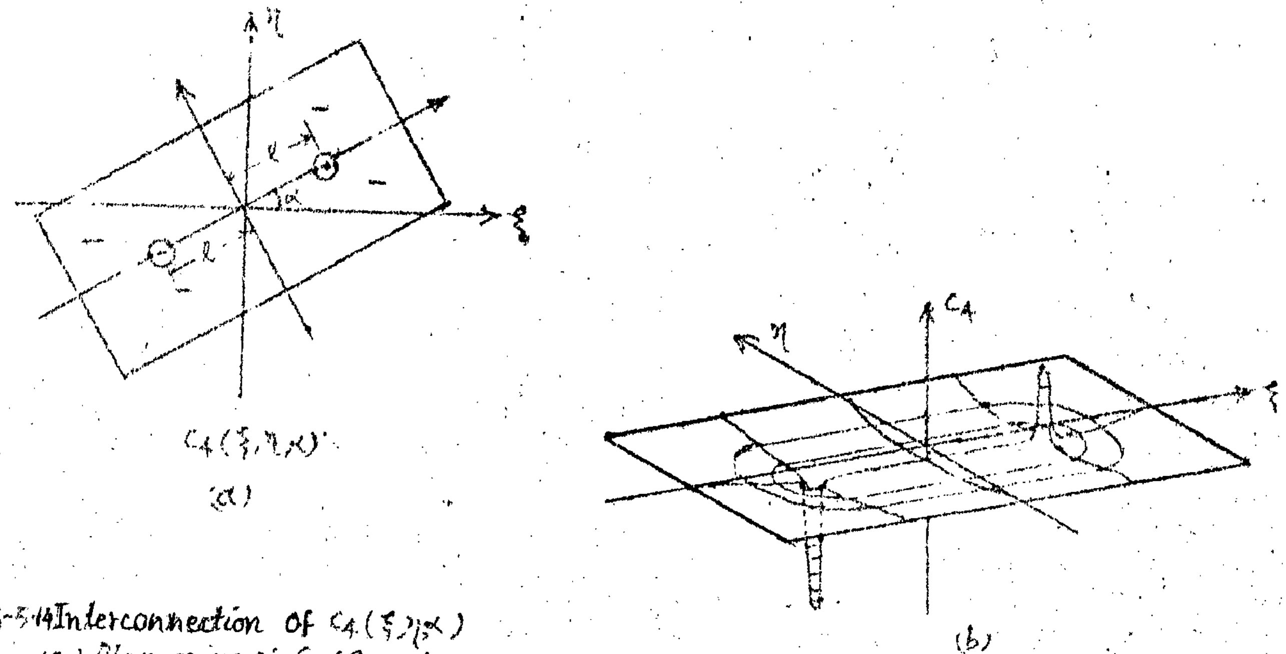


FIG-5.14 Interconnection of $C_4(\xi,\eta,\alpha)$
(a) Plan view of $C_4(\xi,\eta,\alpha)$
(b) Three-dimensional view of the function $C_4(\xi,\eta,0)$

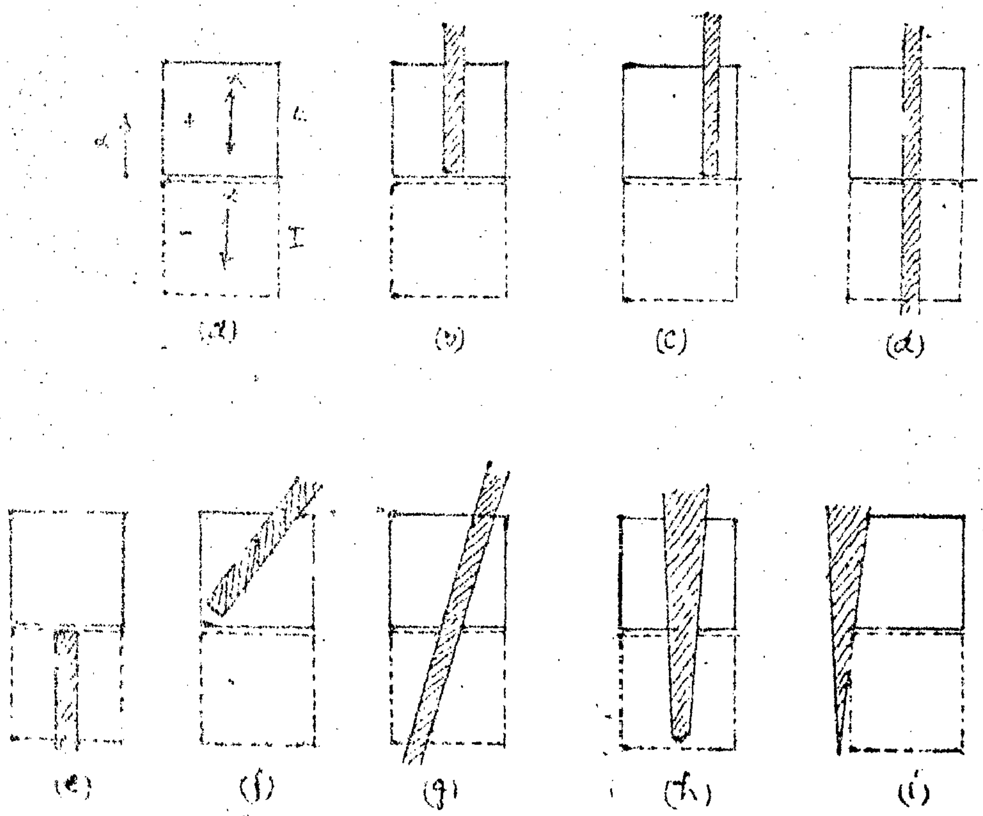


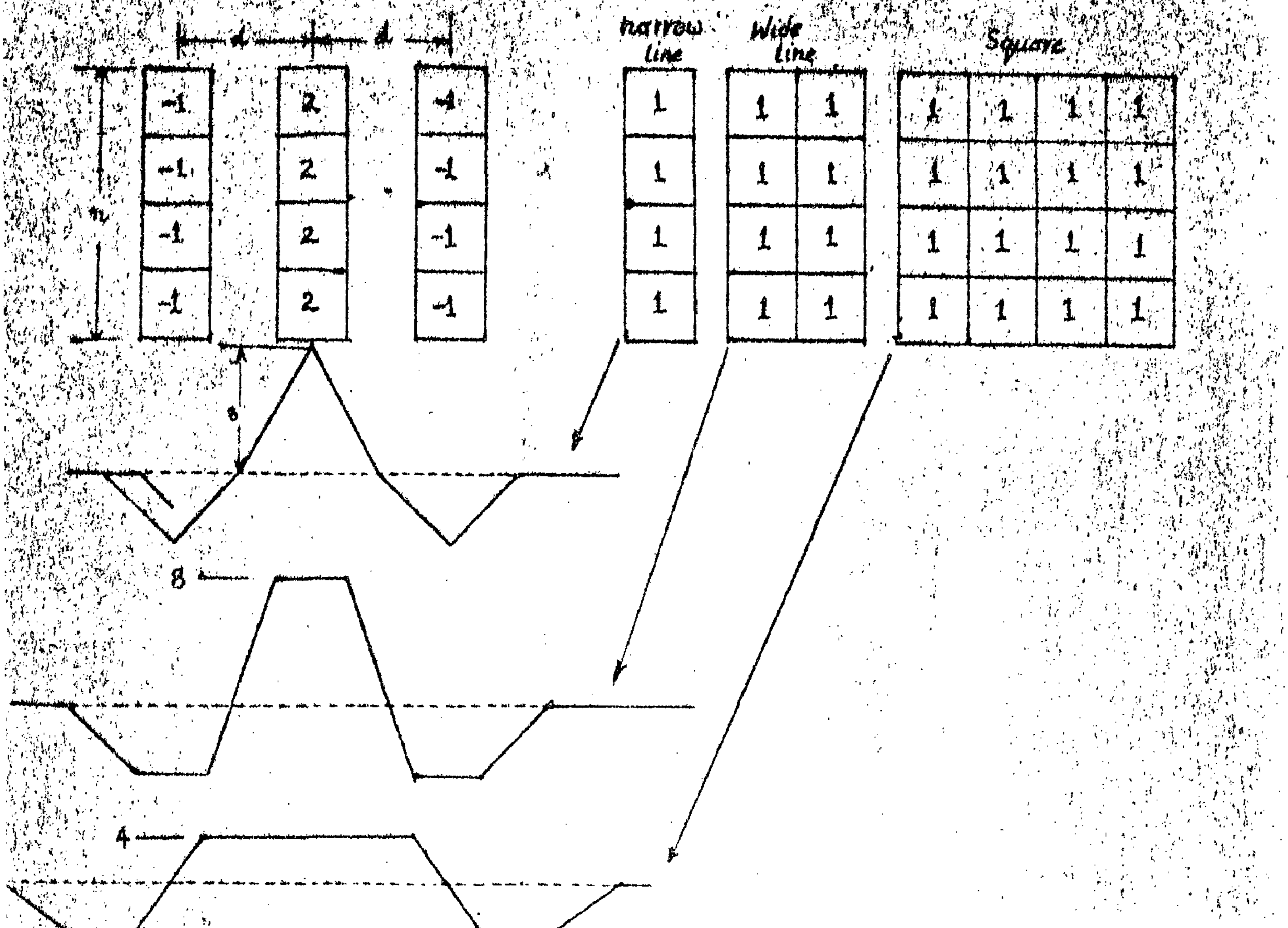
FIG. 5.15 (a) Receptive field of an end-of-vertical line detecting element $u_4(x,y,\pi/2)$
this element responds to patterns (b) and (c) but not to patterns (d) to (i)

receptors which is flanked on both sides by parallel lines of OFF receptors: Some investigators have found that there is a neutral gap between ON and OFF areas. Fig. (5.16) shows n ON receptors with a weighting factor of 2, flanked on both sides by n OFF receptors, with a weighting factor of -1 and at a center to center spacing of d units away from the ON receptors. The weighting factors are chosen so that broad excitation of the entire array, as well as its convolution with long orthogonal lines yields net zero output.

Optimum Relationship Between n and d

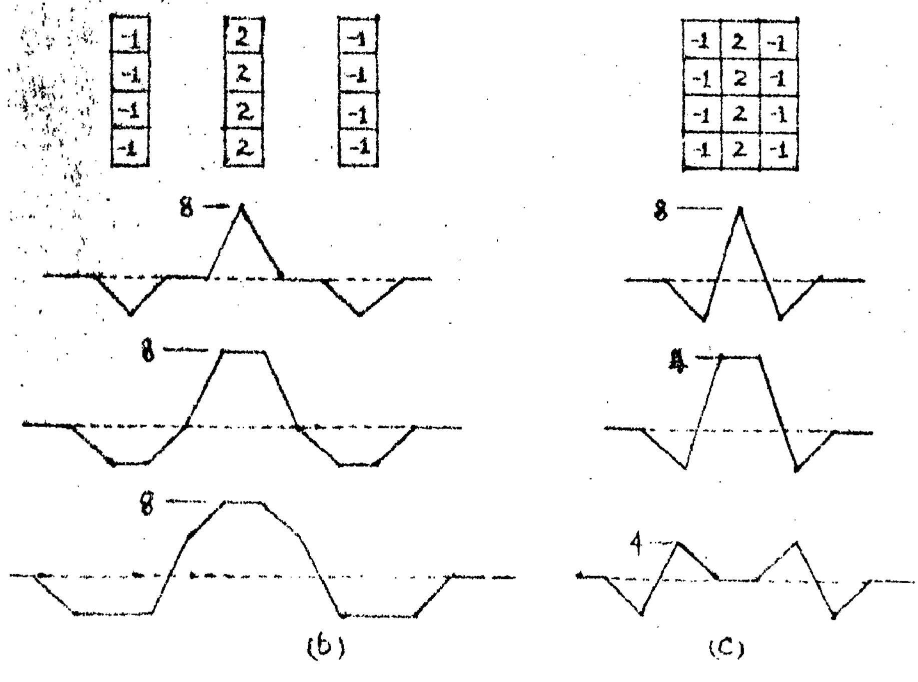
Because human eye is in constant involuntary motion, with peak to peak amplitude of about 20 cones correlative scanning interia seem to be justified. Fig. (5.16a) shows three curves which are a plot of the convolution of feature extraction model when n = 4, d = 2 with various simple geometric patterns. First curve is the convolution with a short line of excitation that exactly matches the ON receptors. As the line moves from right to left across the field the peak values are + 8 and -4. second curve, where excitation pattern is broad line displays broad peak value of +8. The third curve is the result of a square pattern which is featureless since this pattern does not contain a short line of excitation. The feature extraction model is capable of rejecting the square because its peak value is only four.

Then d is increased to 3 units as shown in Fig. (5.16b), then the model fails to reject the square, when d is made 1 unit fig(5.16c) the model becomes too specific and fails to recognize



(a)

FIG-5.16 Wave shapes for the receptor arrays with a given visual pattern (narrow line, wide line, or Square) moving horizontally across the receptor array (a) $n=4, d=2$ (b) $n=4, d=3$, (c) $n=4, d=1$



broad excitation. The $d = n/2$ relationship represents a reasonable compromise because it yields a flat topped half amplitude curve to an $n \times n$ square but full amplitude in response to a line witdth $\leq n-1$ we will consider feature extraction capabilities of smallest receptor group where $n = 2$, $d = 1$ but it can be extended for larger values of n for extracting long lines. In a hypothetical physical model (Fig. 5.17) receptor group feeds a short line extractor neuron (SLEN) in which weighting functions are synaptic junction coefficients of inputs. SLEN discharges when the net input exceeds some positive threshold level.

Topologically there are 23 ways in which 6 receptors of $n = 2$, vertical SLEN can be excited as shown in Fig. (5.18) in the decreasing order of synaptic junction stimulation (exciting pattern is shown black). The net input = 4 is a pattern of exact match with vertical short line for $n = 2$. Net input e.g. corresponds to a corner that will also be recognized by a horizontal SLEN. The first pattern in the net input = 2 row is a dot that should be enhanced by receiving horizontal as well as vertical SLEN recognition same is true with next pattern 2 x 2 square. The first pattern in net input = 1 row is a horizontal line, that should be rejected. The SLEN should operate then for a threshold between 1 and 2. A value slightly greaterthan 1 is assumed as threshold.

Recognition of Decimal Digits

Now we apply the SLEN concept for pattern recognition of simple visual pattern. The 10 decimal digits[Fig. (5.19)] each drawn in a rectangle of ~~with~~ 3 by 5 ~~rectangle~~ is offered as a set of patterns. Some of these patterns differ by only a single element as 3 Vs 9, 5 Vs 6, 8 Vs 9 and 8 Vs 0 : successful visual pattern recognition scheme must be able to distinguish each of those pattern from others. Each of the 3 by 5 rectangles is processed by 9 vertical and 10 horizontal SLENS of Fig. (5.20). only two ON receptors of each SLEN are shown in Fig. and the off receptors are not shown to avoid confusion because of overlapping. The center of the visual field feeds SLENS 5 and 14 each with a weighting factor of 2 while at the same time feeding into SLENs 4,6,13 and 17 each with a weighting factor of -1. Net excitation due to each element in the visual field is zero, which can be the basis for automatic gain control mechanism. The excess SLENS are distributed uniformly throughout the periphery, which take into account the odd dimensions of the patterns.

The matrix which shows net input i.e. net synaptic junction excitation of each test pattern is shown in table I. All values from -4 to +4 are shown except-3. Ten peripheral SLENs 6 vertical and 4 horizontal have been omitted in Fig. (5.20). Considering these also 3 by 5 field is covered completely and algebraic sum of each matrix now becomes zero, which was fundamental assumption. If net synaptic junction excitation increases, net output increases. Considering threshold value 1, net input 4 will produce output corresponding input 3 and net input 2 gives output corresponding to input 1 etc. when the input exceeds the threshold level, SLEN

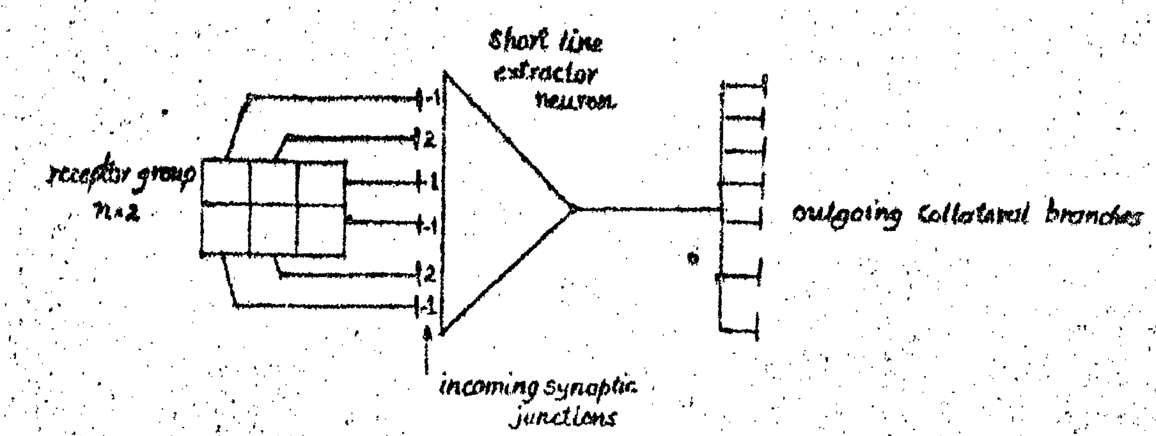


FIG- 5.17 Hypothetical model of n=2 short line extractor neuron

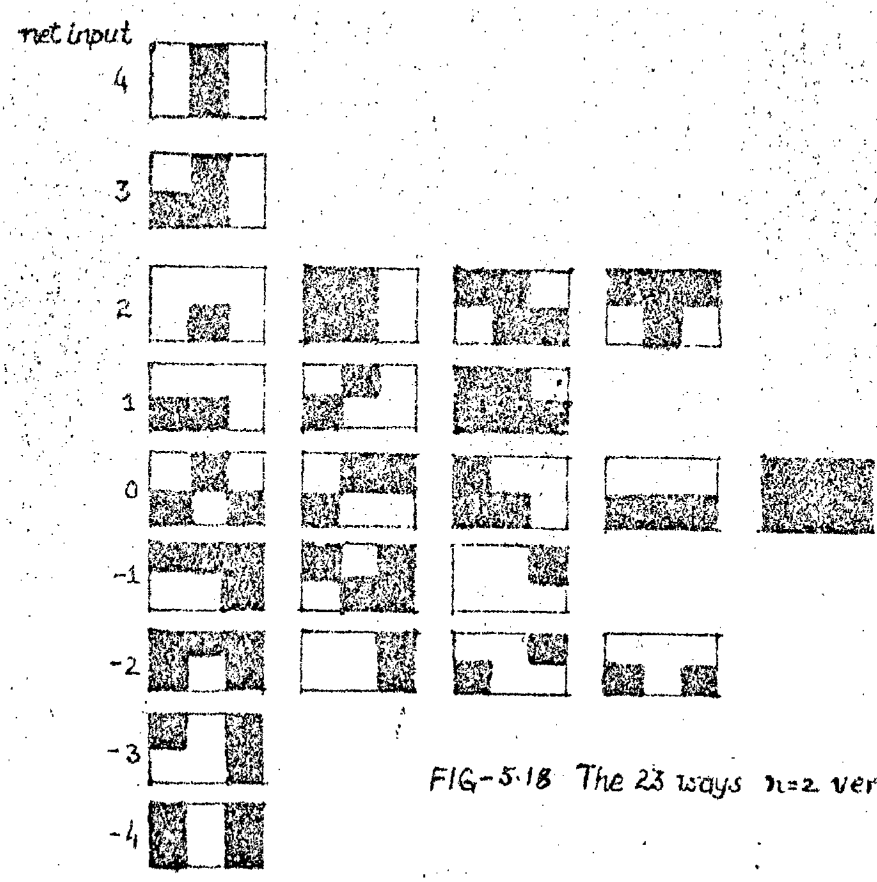


FIG-5.18 The 23 ways n=2 vertical SLEN can be excited

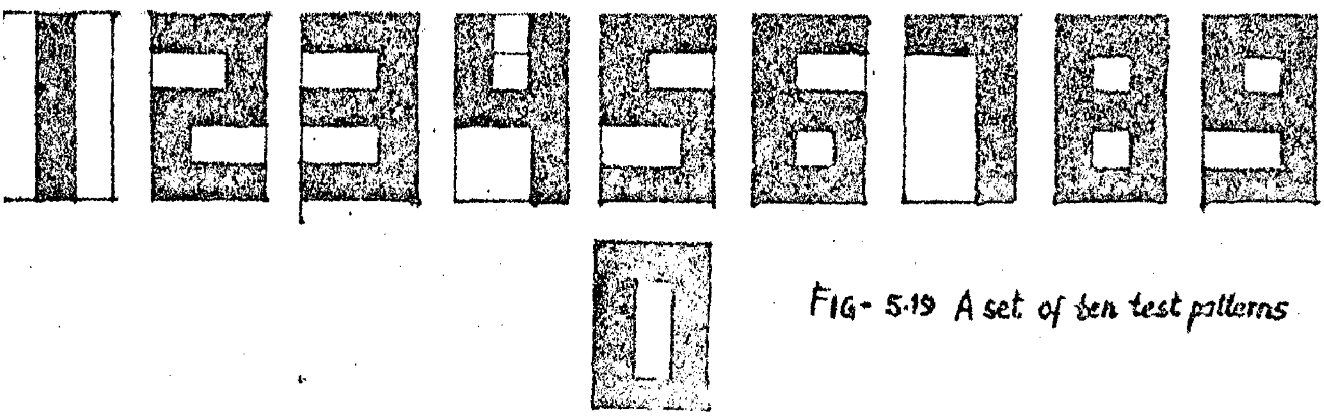


FIG- 5.19 A set of ten test patterns

fires at a uniform rate corresponding to net input i.e. (input minus threshold) value. Then we derive SLEN discharge matrix in which 1 represents firing of the SLEN due to net input 2,3 or 4 (table II). As is obvious 6 of the SLENS never fire, so only 13 SLENs would be sufficient for Test patterns.

We employ 'all-or-nothing' characteristic for the elements to extract features and recognize patterns despite very wide range of sensory receptor stimulus. A reconstruction of each pattern utilising only extracted features from SLEN discharge matrix, should correlate reasonably well with the original pattern Fig. (5.21) shows the reconstructed patterns from extracted features. The error in recognition of the pattern is tolerable keeping in view the brick like geometry of the SLEN arrangement selected.

Learning

We come next to the learning and recognition of patterns. All the feature extraction-neurous form synaptic junctions with memory neurons. For simplicity we can consider a single memory neuron connected through 19 synaptic junctions to the 19 feature-extraction neurons. The junctions of ignorant memory are assumed with a weighting factor of -1 at the synaptic junction of memory neuron. During learning process these inhibitory junctions of -1 become excitatory with weighting factor (+1) because of the firing of that particular feature neuron. Thus memory neuron Fig. (5.21) learns the input pattern and can be used for recognition later on. For

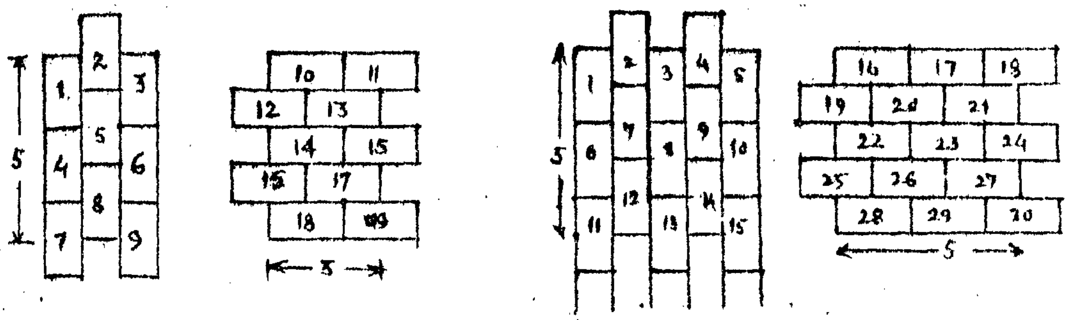
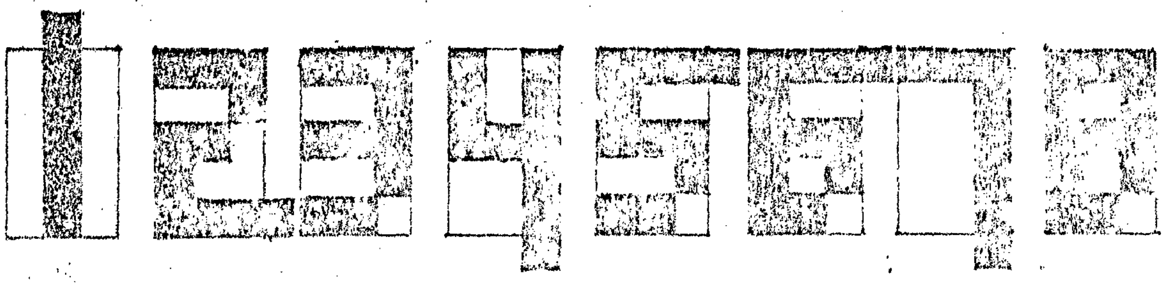


FIG-5.20 Array of 19 SLENs processing 3 by 5 test patterns and 5 by 5 test patterns.



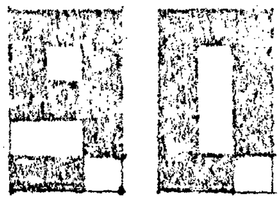


FIG-5.21 Reproduction of ten test patterns

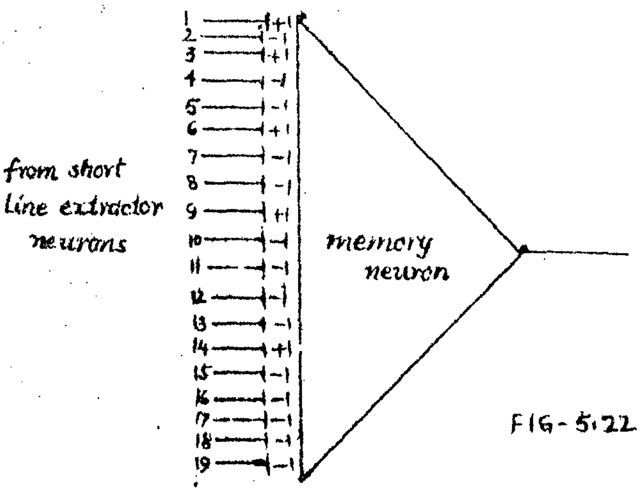


FIG-5.22 Memory neuron that has learned to recognize test pattern 4 a test pattern 4, input junction 1,3,6,9 and 14 are excitatory while remainder are inhibitory.

Recognition

When an unknown pattern is projected on visual cortex appropriate memory neuron should receive maximum stimulus from SLEN network, thereby evoking recognition of unknown pattern. This process of recognition is very similar to matrix multiplication and is illustrated in ~~Fig.~~ (table 3) for test patterns 4 and 7. The two row matrix is a repeat of the SLEN discharge matrix. The 2-column matrix depicts the synaptic junction weighting factors of memory neuron for test patterns 4 and 7. The memory neuron junction matrix is derived from SLEN discharge matrix by replacing 0 by -1 and exchanging rows and columns. The multiplication of both matrices shows that when input pattern 4 exactly corresponds and enters to the memory neuron containing 4, the net output level produced is maximum i.e. 5 but test pattern other than memory neuron pattern e.g. 7 when enters memory neuron 4 a relatively low output is produced i.e. 2. Maximum output values occur along the main diagonal i.e. when the input pattern exactly matches the memory neuron of the same pattern and both patterns are matched.

Concentrating on test patterns 4 and 7, table(2) they have 3 common features 3 $\binom{1}{1}$, 2 features of pattern 4 which are absent in test pattern 7,2 $\binom{0}{1}$ and feature that test pattern 7 has which is absent in test pattern 4 is 1$\binom{0}{1}$. Therefore, if we could measure the degree to which extent the test pattern are uncorrelated, it will give degree of mismatch between the patterns. Pattern recognition is based on differences, between patterns, their similar features represent dc level which should be blocked. If we subtract the entries of any column from its main diagonal value, we are left only with the summation of feature differences and similarities are cancelled. Thus, we find feature difference matrix, considering again patterns 4 and 7 feature differences are calculated in the first column

$$5-2 = 3\binom{1}{1} + 2\binom{1}{0} - 3\binom{1}{1} + 1\binom{0}{1}$$
$$= 2\binom{1}{0} + 1\binom{0}{1}$$

similarly in the second column

$$4-1 = 3\binom{1}{1} + 1\binom{0}{1} - 3\binom{1}{1} + 2\binom{1}{0} = 2\binom{1}{0} + 1\binom{0}{1}$$

Thus feature difference matrix is symmetrical. By generalising the case for two patterns X and Y we can form a 2-row SLEN discharge matrix in which features are grouped in accordance with $a\binom{1}{1}$, $b\binom{1}{0}$ $c\binom{0}{1}$, $d\binom{0}{0}$. Multiplying this 2-row matrix by the 2-column memory neuron junction matrix yields $\begin{bmatrix} a+b & a-b \\ a-c & a+c \end{bmatrix}$ and subtracting entries of a column from its main diagonal element $\begin{bmatrix} 0 & b+c \\ b+c & 0 \end{bmatrix}$ which is symmetrical about main diagonal.

Table II shows the product of entire SLEN discharge matrix and memory neurons junction matrix, and then feature difference matrix is derived from it, table (IV). The four 1 values in the feature-difference matrix correspond to the input patterns which differ by one feature from the pattern corresponding to main diagonal element.

In the same way the 26 letters of the alphabet fig(5.23) can be learned and recognized. The letters are written in a 5 by 5 rectangle as shown in Fig. (5.20). In order the cover the visual field of this rectangle completely, we require 15 horizontal and 15 vertical SLENs. The excess SLENs are uniformly distributed over the periphery of the visual field. Again the inhibitory or OFF receptors are not shown in order to avoid confusion due to overlapping and only ON receptors of each SLEN are shown. The net excitation due to each element of the visual field is zero. The net SLEN input matrix is shown in table (V). Each entry gives net synaptic junction excitation for each test pattern and varies within limits -4 to +4. Considering threshold valve of each SLEN input to be slightly more than 1 only, those SLENs fire which have net input equal to more than 1 i.e. 2,3 and 4 and all the SLENs with net input 1 or less than one will produce no output. By net input SLEN matrix we deduce SLEN discharge matrix table (VI). With zeros showing that corresponding SLEN does not fire. Using SLEN discharge matrix, the extracted features of the test pattern are associated and should match input test pattern closely fig(5.24) i.e. should not produce confusion between the two patterns. The association of extracted features of input Test patterns shows that patterns are reasonably correlated with the patterns deduced from the extracted features of the input pattern by SLEN matrix so that an incoming pattern that exactly matches is synaptic

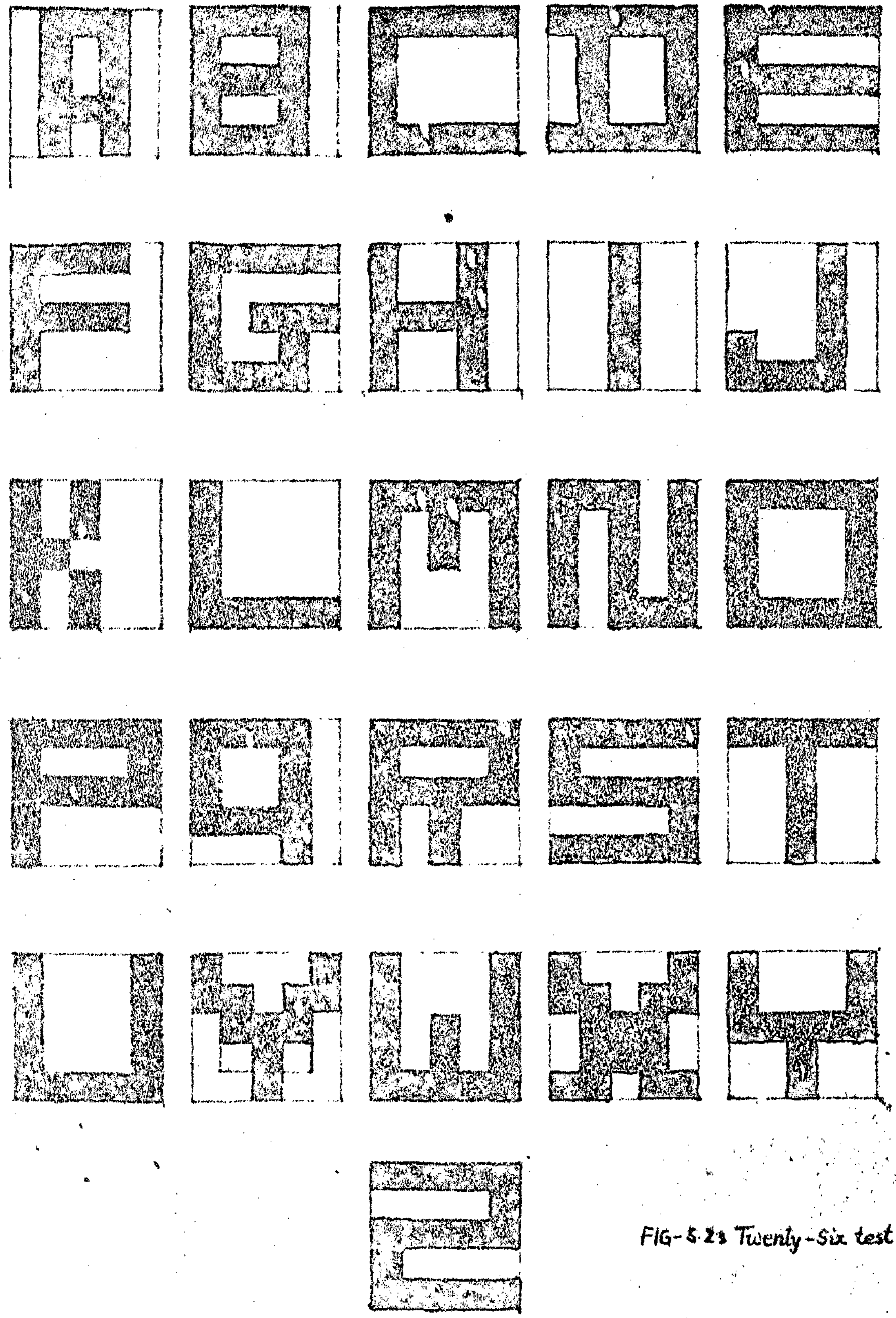


FIG-5.2: Twenty-Six test patterns

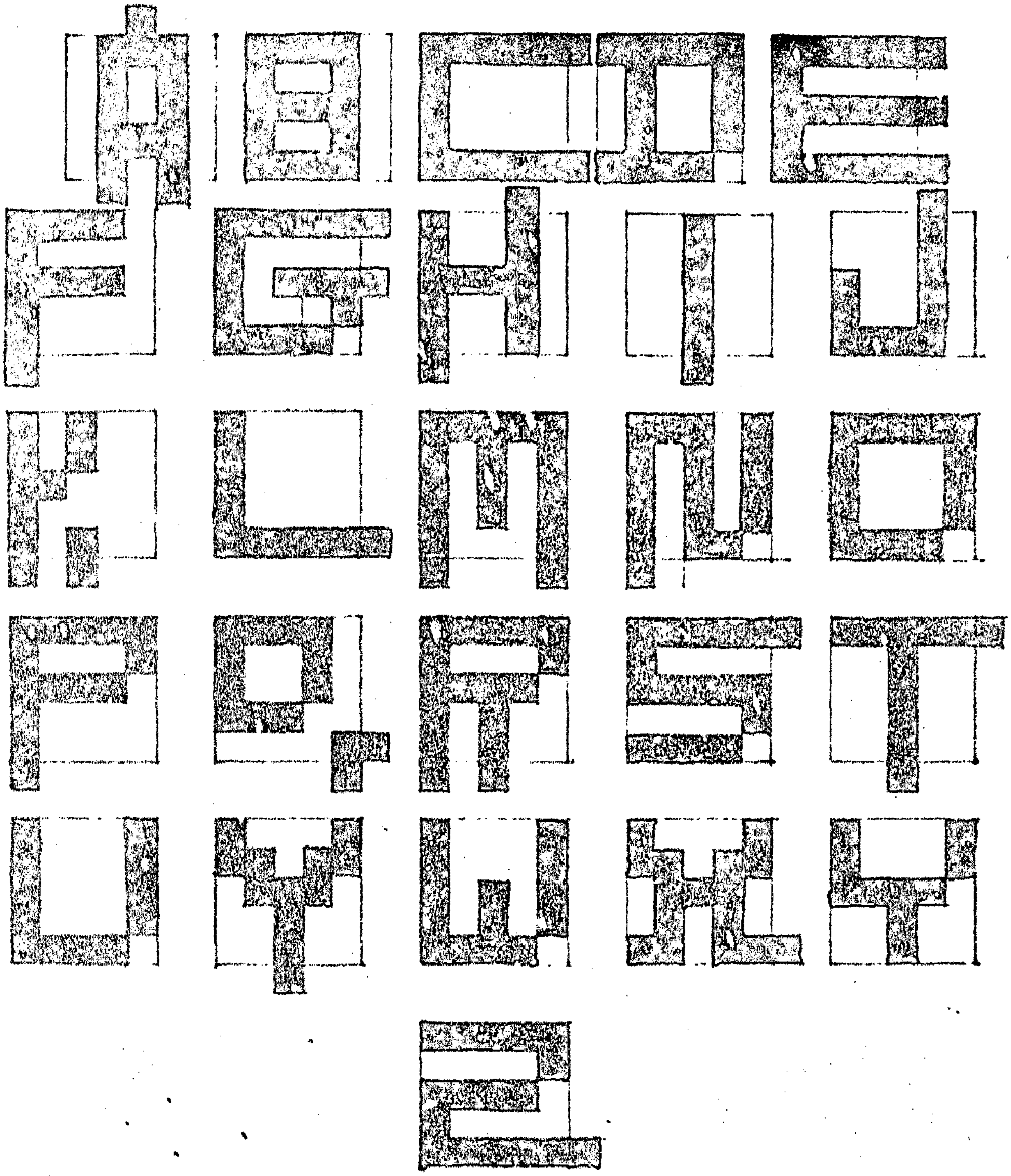


FIG-5.24 Reconstruction of the 26 patterns junction distribution results in a maximum discharge rate of say 1000 Cps. All memory neurons are clamped to the same maximum discharge rate which corresponds to zeros of the main diagonal of the feature difference matrix.

Now consider the learning and recognition of syllab~~u~~les (i.e. groups of letters) and sentences. There is first a layer of SLENs which gives output corresponding to the input pattern. Some SLENs are fired and some remain unfired or unexcited, in response to the net input of each SLEN. These outputs are then connected to the first layer of memory neurons which form synaptic junctions with the SLENs. The weighting factor of each input for the memory neuron is -1 or +1, decided by whether the input SLEN has not fired or fired, respectively. The fired SLEN is shown in the matrix by 1 and unfired by zero.

The output of this memory neuron, as discussed earlier depends upon whether the input pattern matches the pattern for which this memory neuron is meant i.e. according to which its threshold value is set, during learning session. If the input pattern matches the pattern stored by memory neuron, this memory neuron is fired and produces output. Thus our input letter i.e. pattern is recognized perfectly well. Now different memory neurons of this layer are AND gated or may be said to be connected synaptically to memory neuron of the next layers which stores the complex patterns i.e. syllab~~u~~les. This layer gets input from previous memory neurons and weighting factors are again decided +1 or -1 by whether the input memory neuron has fired or not. If all the inputs to this second memory neuron i.e. are in 1 position, in terms of binary algebra, this second neuron fires. The threshold of this neuron is set to the values which corresponds to the maximum input caused by perfect recognition of the patterns by previous neurons.

Thus if any neuron of the second layer fires it is obvious that all the input patterns, whose corresponding outputs were connected to this memory neuron are matched and we conclude that the syllable, composed of those input patterns is identified. For example 'BOY' is to recognized. The patterns B, O, and Y will produce maximum outputs for those memory neurons of first layer, which are meant for these letters, respectively. Now all these three neurons are connected to other memory neuron. If B, O and Y are recognized perfectly, the outputs from those neurons were maximum and hence the inputs of this second memory neuron attain a weighting factor of +1 at its input synaptic junctions. Under perfect matching of B, O and Y, this memory neuron will produce maximum output which indicates recognition of the syllable. The irregularities in the deduced patterns, compared to the original test pattern, are due to brick like structure of the SLEN rectangle assumed.

Now we will consider how learning and recognition of test patterns occur? Again assuming, similar to the numerals recognition, that every feature extractor neuron forms a synaptic junction with the memory neuron. So a single memory neuron has 30 inputs, each connected to the feature extracting neuron with connection coefficient of -1 for the unfired SLEN and +1 for fired neuron. Say considering patterns P to be learned, memory neuron has certain ~~following~~ configuration. Memory neuron matrix for all the test patterns is shown in table (VII). Thus each memory neuron is meant to store features of a particular test pattern and produces maximum output for that pattern. Considering pattern P and F. If pattern P is projected to the SLEN matrix of horizontal and vertical SLEN then the memory neuron corresponding to P will generate output 8 while memory neuron F generates 7 for an input pattern F. But if P enters the memory neuron F only 6 output is produced.

For recognition the multiplication of the SLEN discharge matrix and memory neuron matrix is performed. Memory neuron matrix is derived from SLEN discharge matrix by replacing 0's by -1's corresponding to unfired neurons and changing rows into columns. The product of these matrices is shown in table (VIII). Then by substracting the entries of each column of this product matrix from main diagonal entry we get feature, difference matrix (table IX). Feature difference matrix shows the feature differences of the patterns, it has all maindiagonal elements zero. It shows the degree to which the pattern features are uncorrelated. The more the values of features difference matrix, more is probability of correct recognition of the patterns. The values 1 in feature difference matrix show that there is small degree of separability in recognition of those two input patterns.

This method of matrix multiplication for recognition of patterns and subtraction steps are within the realm of possibility for the mammalian visual cortex. As a part of its learning process the memory neuron threshold level is automatically set.

Step Number

Test pattern	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	-2	2	-2	-2	4	-2	-1	4	-1	1	0	0	0	0	0	0	0	1	0
2	1	0	3	3	-1	1	+1	-1	1	4	1	-2	-2	3	1	0	-4	3	2
3	1	0	3	1	-1	3	1	-1	1	4	1	-2	-2	4	0	-2	-2	4	1
4	4	-2	4	1	-2	3	0	-2	2	1	1	0	-1	3	0	-1	-1	0	1
5	3	0	1	1	-1	3	1	-1	1	3	2	0	-4	3	1	-2	-2	4	1
6	3	0	1	3	-1	3	1	-2	1	3	2	0	-4	2	1	0	-2	3	1
7	1	0	3	0	-2	4	0	-2	2	4	1	-1	-1	0	0	0	0	0	1
8	3	0	3	3	-2	3	1	-2	1	3	1	0	-2	2	0	0	-2	3	1
9	3	0	3	1	-2	3	1	-1	1	3	1	0	-2	3	0	-2	-2	4	1
0	3	0	3	4	-4	4	1	-2	1	3	1	0	-1	0	0	0	-1	3	1

Table - 2. **SLEN DISCHARGE MATRIX**

SLEN Number

est
a-
tern

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2	0	0	1	1	0	0	0	0	0	1	0	0	0	1	0	0	0	1	1
3	0	0	1	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0
4	1	0	1	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0
5	1	0	0	0	0	1	0	0	0	1	1	0	0	1	0	0	0	1	0
6	1	0	0	1	0	1	0	0	0	1	1	0	0	1	0	0	0	1	0
7	0	0	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0	0	0
8	1	0	1	1	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0
9	1	0	1	0	0	1	0	0	0	1	0	0	0	1	0	0	0	1	0
0	1	0	1	1	0	1	0	0	0	1	0	0	0	0	0	0	0	1	0

Table - 3. PRODUCT OF SLEW DISCHARGE MATRIX AND MEMORY NEURON JUNCTION MATRIX

		Memory Neuron Pattern									
		1	2	3	4	5	6	7	8	9	0
Test Pattern	1	3	-3	-3	-3	-3	-3	-3	-3	-3	-3
	2	-6	6	2	-2	0	2	-2	4	2	2
	3	-5	3	5	1	3	3	1	5	5	3
	4	-5	-1	1	5	1	1	1	3	3	1
	5	-6	0	2	0	6	6	-2	4	4	2
	6	-7	1	1	-1	5	7	-3	5	3	3
	7	-4	0	2	2	0	0	4	2	2	2
	8	-7	3	3	1	3	5	-1	7	5	5
	9	-6	2	4	2	4	4	0	6	6	4
	0	-6	2	2	0	2	4	0	6	4	6

Table No.4 Feature Difference Matrix

Memory neuron Pattern

2	3	4	5	6	7	8	9	0
9	8	8	9	10	7	10	11	9
0	3	7	6	5	6	3	4	4
3	0	4	3	4	3	2	1	3
7	4	0	5	6	3	4	3	5
6	3	5	0	1	6	3	2	4
5	4	6	1	0	7	2	3	3
6	3	3	6	7	0	5	4	4
3	2	4	3	2	5	0	1	1
4	1	3	2	3	4	1	0	2
4	3	5	4	3	4	1	2	0

Table - V.

MEMORY NEURON MATRIX

Test patterns

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
1	1	1	-1	1	1	1	1	-1	-1	1	1	1	1	1	1	1	1	1	-1	1	1	1	1	1	-1
1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
1	-1	-1	-1	-1	-1	-1	-1	1	-1	1	-1	1	1	-1	-1	-1	-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	-1	+1	-1	-1	1	1	1	1	1	1
1	1	1	-1	1	1	1	1	-1	1	1	1	1	1	1	1	1	1	-1	-1	1	-1	1	-1	-1	1
-1	-1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	1	-1	-1
1	-1	-1	-1	-1	-1	-1	-1	1	-1	-1	-1	1	1	-1	-1	-1	1	-1	1	-1	1	1	-1	1	-1
-1	1	-1	-1	-1	-1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	1	-1	-1	-1	-1	1	-1	1	-1	-1
-1	-1	-1	1	-1	-1	1	-1	-1	-1	-1	-1	1	1	1	-1	-1	-1	1	-1	1	-1	1	-1	-1	-1
1	-1	-1	-1	-1	1	-1	1	-1	-1	1	-1	1	1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	-1
1	-1	-1	-1	-1	-1	-1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	1	-1	1	-1	1	-1	-1	1	-1
-1	1	-1	-1	-1	-1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	-1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1
1	1	1	1	1	1	1	-1	-1	-1	-1	-1	1	1	1	1	1	1	1	1	-1	-1	-1	-1	-1	1
-1	1	1	1	1	1	1	-1	-1	-1	-1	-1	1	-1	1	1	1	1	1	1	-1	-1	-1	-1	-1	1
-1	-1	1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	-1	-1	1	-1	-1
-1	1	-1	-1	1	1	-1	1	-1	-1	1	-1	-1	-1	-1	1	-1	1	1	-1	-1	-1	-1	-1	1	1
-1	1	-1	-1	1	1	1	1	-1	-1	-1	-1	-1	-1	-1	1	-1	1	1	-1	-1	1	-1	1	1	1
-1	-1	-1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	1	1	1	1	-1	1	-1	-1	1	-1	1	-1	-1	1	-1	-1	-1	1	-1	1	-1	1	1	-1	1
-1	1	1	1	1	-1	1	-1	-1	1	-1	1	-1	1	1	-1	-1	-1	1	-1	1	-1	1	-1	-1	1
-1	-1	1	-1	1	-1	-1	-1	-1	-1	-1	1	-1	-1	-1	-1	1	-1	-1	-1	-1	-1	-1	1	-1	1

Table - 5. [illegible]

Letters	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
A	1	1	1	0	0	1	0	1	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
B	1	0	0	0	0	1	0	0	1	0	0	0	0	1	0	1	1	0	0	0	0	1	1	0	0	0	0	1	1	0
C	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1
D	0	0	0	0	1	0	1	0	0	1	0	1	0	0	0	1	1	0	0	0	0	0	[illegible]	[illegible]	[illegible]	0	0	1	1	0
E	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	1	1	1	0	0	0	1	1	1
F	1	0	0	0	0	1	0	[illegible]	0	0	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0
G	1	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	0	1	1	0	0	0	1	1	1
H	1	0	0	1	0	1	0	0	1	0	1	0	0	1	0	0	0	0	0	0	0	1	1	0	0	0	[illegible]	0	[illegible]	0
I	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	[illegible]	0	0	0	0	0	0	0	0
J	0	0	0	1	0	1	0	0	1	0	0	0	0	1	0	0	0	0	[illegible]	0	0	0	0	0	0	0	0	0	0	0
K	1	0	1	0	0	1	0	0	[illegible]	0	1	0	1	0	0	0	0	0	0	[illegible]	[illegible]	1	0	0	0	0	0	0	0	0
L	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
M	1	0	1	0	1	1	0	1	0	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
N	1	0	1	0	1	1	0	1	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0
O	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	1	0
P	1	0	0	0	1	1	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0
Q	1	0	0	0	0	1	0	0	1	0	0	0	0	0	1	1	1	0	0	[illegible]	0	0	0	0	0	0	0	0	0	1
R	1	0	0	0	1	1	0	1	0	0	1	0	1	0	0	1	1	0	0	0	0	1	1	0	0	0	0	0	0	0
S	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	1	1	0	0	0	1	1	0	0	0	0	1	1	0
T	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
U	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	[illegible]	0	0	0	[illegible]	0	0	0	0	1	1	0
V	1	0	0	0	1	0	1	1	1	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0
W	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	[illegible]	0	[illegible]	[illegible]	0	[illegible]	0	0	0	0	0	1	1	0
X	1	0	0	0	1	0	1	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	1	0	1
Y	1	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
Z	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	1	1	0	0	0	0	1	1	1

SLAN NUMBER

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
A	3	2	3	-1	0	3	-4	3	-2	0	2	-2	2	-2	0	3	1	0	0	-1	0	-1	0	0	0	2	0	1	1	0
B	3	0	-1	+1	-2	3	-1	-1	+3	-2	1	-1	0	+3	-1	3	4	0	0	-4	0	2	2	0	0	-4	0	3	3	0
C	3	0	0	1	-1	4	-2	0	0	0	1	0	0	1	-1	3	4	2	0	-2	-2	0	0	0	0	0	0	3	4	2
D	0	0	-1	0	3	-2	4	-2	-2	4	1	2	0	0	1	3	4	1	-1	0	0	0	0	0	-1	0	-1	3	4	1
E	3	0	0	0	1	3	-1	0	0	1	1	0	0	0	1	3	4	2	0	-4	-4	2	4	2	0	-4	-4	3	4	2
F	3	0	0	1	-1	3	0	0	1	-1	2	-1	0	0	0	3	4	0	0	-4	-2	2	4	0	0	-2	-1	1	0	0
G	3	0	0	0	-1	4	-2	-1	1	3	1	0	0	-1	1	3	4	2	0	-2	-2	0	2	2	0	-2	-2	3	4	1
H	4	-1	-2	2	-2	[illegible]	-1	0	3	-2	2	-2	-1	3	-1	1	1	0	0	-2	1	2	2	0	0	-2	0	1	1	0
I	0	-1	4	-1	0	[illegible]	-2	4	-2	0	0	-2	2	-2	0	0	-1	0	0	0	0	0	0	0	0	0	0	0	1	0
J	0	0	-2	2	-2	4	-1	-2	4	-2	1	0	0	3	-1	0	1	0	0	0	0	1	0	0	0	-2	0	3	3	0
K	4	-2	+4	-1	0	3	-1	1	-1	0	2	-4	+2	-2	0	1	1	0	0	0	0	[illegible]	-2	0	0	0	0	1	1	0
L	4	-1	0	0	0	4	-2	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	-2	-2	3	4	2
M	3	0	2	0	3	4	-4	4	-4	4	[illegible]	-3	0	-3	2	3	3	1	0	-1	-1	0	0	0	0	-1	0	1	1	1
N	3	0	3	-1	4	4	-4	4	-4	4	2	-4	+1	-1	1	3	1	1	0	0	0	0	0	0	0	0	-1	1	3	1
O	3	0	0	0	3	[illegible]	-2	0	-2	4	1	0	0	0	1	3	4	1	0	-2	-1	0	0	0	0	-2	-1	3	4	1
P	3	0	0	0	3	3	-1	0	-1	1	2	-2	0	0	0	3	4	1	0	-4	-1	2	4	1	0	-2	-2	1	0	0
Q	3	0	0	1	-2	4	-2	-1	+4	-2	0	0	0	1	2	3	4	0	0	-2	0	0	0	0	1	4	1	-2	-2	2
R	3	0	0	0	3	3	0	2	0	1	2	-4	2	-2	0	3	4	1	0	-4	-2	2	3	1	0	-1	-2	1	1	0
S	3	0	0	0	1	1	0	0	0	[illegible]	1	0	0	0	1	3	4	2	0	-4	+4	3	4	1	-2	-4	-2	4	4	1
T	1	0	2	0	1	0	-2	4	-2	0	0	-2	2	-2	0	4	3	2	-1	-1	-2	0	0	0	0	0	0	0	1	0
U	4	-1	0	-1	4	4	-2	0	-2	4	1	-1	0	-1	1	1	0	1	0	0	0	0	0	0	0	-2	-1	3	4	1
V	3	-1	0	-1	4	-1	2	2	2	-1	0	-2	2	-2	0	0	0	1	1	0	2	1	2	0	0	0	-1	0	1	0
W	4	-1	0	-1	4	4	-3	4	-2	4	1	0	0	0	1	1	0	1	0	-1	0	0	[illegible]	0	0	-1	-1	3	3	1
X	3	-1	-2	-1	+3	-2	2	0	2	-2	1	2	-2	2	1	0	-1	1	1	0	2	-1	2	-1	-1	1	-1	3	0	2
Y	4	0	0	-1	4	1	0	2	-1	1	0	-2	2	-2	0	1	0	1	0	-2	-1	3	3	1	-1	0	-2	0	1	0
Z	1	0	0	0	3	3	0	0	-1	1	1	-1	0	0	1	4	4	1	-2	-4	-2	3	4	1	0	-4	-4	3	4	2

Table -5 SLAN net input matrix

0	13	11	15	14	8	13	11	6	13	5	10	7	6	11	9	10	7	14	7	11	11	10	17	9	14
13	0	6	10	5	5	6	6	13	6	10	7	12	11	6	6	7	8	5	12	8	12	9	10	10	5
11	6	0	8	3	7	4	12	11	8	10	3	10	9	5	8	5	10	5	8	6	14	7	12	12	5
15	10	8	0	11	11	8	12	11	10	14	9	10	9	4	10	11	12	7	10	6	12	7	10	12	7
14	5	3	11	0	6	3	11	14	11	11	6	13	12	7	7	8	9	4	11	9	15	10	13	11	4
8	5	7	11	6	0	7	5	10	11	5	8	7	8	7	1	6	3	6	9	9	11	10	13	7	6
13	6	4	8	3	7	0	12	13	10	12	7	10	9	4	8	9	10	3	10	6	14	7	14	12	7
11	6	12	12	11	5	12	0	11	6	6	9	12	11	12	6	9	8	11	14	10	10	11	10	8	11
6	13	11	11	14	10	13	11	0	9	5	8	9	8	11	11	10	9	12	3	9	7	8	13	5	12
13	6	8	10	11	11	10	6	9	0	10	5	14	11	8	12	9	14	11	12	6	12	7	10	12	9
5	10	10	14	11	5	12	6	5	10	0	7	8	7	10	8	9	6	11	8	8	10	9	14	6	11
10	7	3	9	6	8	7	9	8	5	7	0	11	8	5	9	6	11	8	11	3	11	4	9	9	6
7	12	10	10	13	7	10	12	9	14	8	11	0	3	6	6	7	6	11	8	8	12	7	16	10	11
6	11	9	9	12	8	9	11	8	11	7	8	3	0	5	7	10	7	10	9	5	11	4	15	9	10
11	6	5	4	7	7	4	12	11	8	10	5	6	5	0	6	7	8	5	10	2	12	3	12	10	5
9	6	8	10	7	1	8	6	11	12	8	9	6	7	6	0	7	2	7	10	8	10	9	12	6	5
10	7	5	11	8	6	9	9	10	9	9	6	7	10	7	7	0	9	10	9	9	11	10	11	11	8
7	8	10	12	9	3	10	8	9	14	6	11	6	7	8	2	9	0	9	8	10	8	9	14	4	7
14	5	5	7	4	6	3	11	12	11	11	8	11	10	5	7	10	9	0	9	7	13	8	13	9	6
7	12	8	10	11	9	10	14	3	12	8	11	8	9	10	10	9	8	9	0	12	10	11	16	8	11
11	8	6	6	9	9	6	10	9	6	8	3	8	5	2	8	9	10	7	12	0	10	1	10	8	7
11	12	14	12	15	11	14	10	7	12	10	11	12	11	12	10	11	8	13	10	10	0	9	6	4	13
10	9	7	7	10	10	7	11	8	7	9	4	7	4	3	9	10	9	8	11	1	9	0	11	7	8
17	10	12	10	13	13	14	10	13	10	14	9	16	15	12	12	11	14	13	16	10	6	11	0	10	11
9	10	12	12	11	7	12	8	5	12	6	9	10	9	10	6	11	4	9	8	8	4	7	10	0	9
14	5	5	7	4	6	7	11	12	9	11	6	11	10	5	5	8	7	6	11	7	13	8	11	9	0

memory neuron

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	9	-3	-3	-7	-3	-1	-3	-3	-3	-7	1	-5	3	3	-3	-1	-3	3	-5	-1	-3	-3	-3	-7	-3	-5
B	-4	10	2	-2	6	2	4	2	-10	0	-4	-2	-2	-2	2	2	0	2	4	-6	-2	-4	-2	0	-4	4
C	-2	4	8	0	8	0	6	-4	-8	-2	-4	2	0	0	3	0	2	0	4	-2	0	-6	0	-2	-6	4
D	-6	0	0	8	0	-4	2	-4	-8	-4	-8	-4	0	0	4	-2	-4	-2	2	-4	0	-4	0	0	-6	2
E	-5	8	5	-3	11	1	7	-3	-11	-5	-5	-1	-3	-3	1	1	-1	1	5	-5	-3	-7	-3	-3	-5	5
F	1	5	1	-3	5	7	3	3	-7	-5	1	-3	3	1	1	7	1	7	3	-3	-3	-3	-3	-3	-3	3
G	-4	4	4	0	8	0	10	-4	-10	-4	-6	-2	0	0	4	0	-2	0	6	-4	0	-6	0	-4	-6	2
H	-2	4	-4	-4	0	2	-2	8	-8	0	0	-4	-2	-2	-4	2	-2	2	-2	-8	-8	-2	-4	0	-2	-2
I	3	-3	-3	-3	-3	-3	-3	-3	3	-3	1	-3	1	1	-3	-3	-3	1	-3	3	-3	1	-1	-3	1	-3
J	-4	4	0	-2	0	-4	0	2	-6	6	-4	0	-4	-2	0	-4	-2	-4	-2	-6	0	-4	0	0	-6	0
K	4	0	-2	-6	0	2	-2	2	-2	-4	6	-2	-2	2	-2	0	-2	4	-2	-2	-2	-2	-2	-4	0	-2
L	-1	3	5	-1	5	-1	3	-1	-5	1	-1	5	-1	1	3	-1	1	-1	1	-5	3	-3	3	1	-3	3
M	2	-2	-2	-2	-2	0	0	-4	-6	-8	-2	-6	10	6	2	2	0	4	-2	-2	-2	-4	0	-6	-4	-2
N	3	-1	-1	-1	-1	-1	1	-3	-5	-5	-1	-3	7	9	3	1	-3	3	-1	-3	1	-3	3	-5	-3	-1
O	-2	6	3	4	4	0	6	-4	-8	-2	-6	0	4	4	8	2	0	2	4	-6	4	-4	4	-2	-4	4
P	0	4	0	-2	4	6	2	2	-8	-6	-2	-4	4	2	2	8	0	8	2	-4	-2	-2	-2	-2	0	4
Q	-1	3	3	-3	3	1	1	-1	-7	-3	-3	-1	3	-1	1	1	7	1	-1	-3	-3	-3	-3	-1	-5	1
R	2	2	-2	-4	2	4	0	0	-6	-8	0	-6	4	2	0	6	-2	10	0	-2	-4	0	-2	-4	2	2
S	-6	5	3	1	7	1	7	-3	-9	-5	-5	-3	-1	-1	3	1	-3	1	2	-3	-1	-5	-1	-3	-3	3
T	2	-2	0	-2	0	-2	0	-6	0	-6	-2	-6	2	0	-2	-2	-2	2	0	6	-6	-2	-4	-6	-2	-2
U	-2	2	2	2	2	-2	4	-2	-6	0	-2	2	2	4	6	0	-2	0	2	-6	6	-2	6	0	-2	2
V	-2	-2	-6	-4	-4	-4	-4	-2	-4	-6	-4	-6	-2	-2	-4	-2	-4	2	-4	-4	-4	8	-2	4	2	-4
W	-1	1	1	1	1	-3	3	-3	-5	-1	-3	1	3	5	5	-1	-3	1	1	-5	5	-1	7	-1	-1	1
X	-8	0	-4	-2	-2	-6	-4	-2	-10	-4	-8	-4	-6	-6	-4	-4	-4	-4	-4	-10	-4	2	-4	10	-4	-2
Y	0	0	-4	-4	0	0	-2	0	-2	-6	0	-4	0	0	-2	2	-4	6	0	-2	-2	4	0	0	6	0
Z	-5	8	3	1	7	1	3	-3	-9	-3	-5	-1	-1	-1	3	3	-1	3	3	-5	-1	-5	-1	-1	-3	9

Test Patter...

Table 9- product of [illegible] discharge matrix and memory neuron junction matter matrix

C. Two Stage Feature Extraction of Alphanumeric Patterns for Recognition [13]

This system is proposed for noisy and low resolution measurements. This process is quite simple and can be considered befitting under the constraints, imposed by fast and accurate processing and recognition in human brain. Here the feature extraction for pattern identification takes place in two stages:

1) Primary features

The fundamental primary features to be extracted are stop, branching and union. These are insensitive to the quality and format of a black-white bit pattern. The pattern is projected on vertical arrays of photosensitive elements. Thus the pattern is vertically or horizontally scanned and splitted into black-white vertical or horizontal strips (or in other sense ON-OFF vertically or horizontally arranged neurons

2) Secondary Features

Then we determine a set of properties which is capable of discriminating the character classes. These features are derived from primary features.

The primary features are best defined by employing the vertical or horizontal scanning on the field of view. In the analysis of vertical scanning a segment of black cells is called an element, a collection of intersected elements of specific length is called a group. An element or a group of length greater than some number is called a vertical line.

A stop is an open end of a group, a union is a merging of two groups into one and a branching is a splitting of a ~~groups~~ group into two.

Primary feature detection. Basic information in the analysis of vertical scanning is the observed sequence of elements of a character. Each element is described by a pair of its end coordinates with x indexing the position of scanning. Detection of primary features consists in (1) detecting the presence of features (2) locating the coordinates of the features.

$y(x)$ = lower y coordinate of an element in the x^{th} vertical scanning

$Y(x)$ = upper y coordinate of an element in the x^{th} vertical scanning

$e(x)$ = element in the x^{th} vertical scanning, specified by the values of $y(x)$ and $Y(x)$

$L(x)$ = length of an element in the x^{th} vertical scanning $= Y(x) - y(x)$

$\bar{L}(x)$ = set of numbers consisting of $y(x)$, $y(x)+1$, $y(x)+2$.. $Y(x)-1$, $Y(x) = Y(x) - y(x)$

If we replace y by x and Y by X then all the parameters discussed above also represent coordinates and parameters of the horizontal scanning. We say that there exists branching and the branching point is $D\left(x+1, \frac{Y_1(x+1)+y_2(x+1)}{1}\right)$ if we have have following sequence of elements $e_1(x)$ $e_1(x+1)$, $e_1(x+2)$, $e_2(x+2)$, $e_1(x+3)$, $e_2(x+3)$, furthermore (1) $L_1(x) \cap L_1(x+1)$

for $i = 1,2$ and (2) $L_i(x+1) \cap L_i(x+2) \neq o$, $L_i(x+2) \cap L_i(x+3) \neq o$ for $i = 1,2$. Using analogous condition for union, we detect union and union point is found to be $U(x, (Y_1(x)+y_2(x))/2)$ if the union of the two groups occurs at $(x+1)$

A stop point is called to exist and a stop point is $S(x, (Y(x)+y(x))/2)$ if the element $e(x)$ is the isolated first element orthe isolated last element of a group which is neither vertical nor the constituent of union or branching, we say that there exists a stop point for the vertical line $e(x)$ and the stop points are $S_1(x, Y(x))$ and $S_2(x, y(x))$ if $|Y(x)-Y(x')| > \gamma$ and $|y(x)-y(x')| > \gamma$ for $|x-x'| \leq 2$ r is small specified value.

Primary features for numerals and Alphabetic letters are : Fig(5.25 a & b)

Vertical scanning

Pattern	Pv(s) Stop points	Pv.(U) Union	Pv(b) branching	PH(B)
0	0	1	1	
1	0	0	0	2
2	2	1	1	
3	2	2	1	
4	~~10~~ 0	~~10~~ 0	~~4~~ 0	3
5	2	1	1	
6	1	1	2	
7	1	1	0	
8	0	3	3	
9	1	2	1	

	Vertical scanning			Horizontal scanning		
Pattern	Pv(s)	Pv(u)	Pv(b)	PH(s)	$P_H(u)$	$P_H(b)$
A	2	1	1			
B	0	2	3			
C	2	0	1	2	0	0
D	2	2	1			
E	3	0	2			
F	2	0	1	1	0	0
G	3	1	1			
H	0	0	0	4	1	1
I	0	0	0	2	0	0
J	3	1	0			
K	2	0	1	4	1	1
L	1	0	0			
M	0	0	0	2	2	1
M	0	0	0	2	2	1
N	0	0	0	2	1	1
O	0	1	1	0	1	1
P	0	1	1	1	1	1
Q	1	2	3			
R	1	1	2			
S	2	1	1			
T	2	0	0	1	0	0
U	0	0	0	2	0	1
V	2	0	0	2	0	1
W	0	0	0	2	1	2
X	4	1	1			
Y	2	0	0	3	0	1
Z	2	1	1			

Second Stage of Feature Extraction

From primary features points, we derive secondary features which produce distinctive characteristics of these point

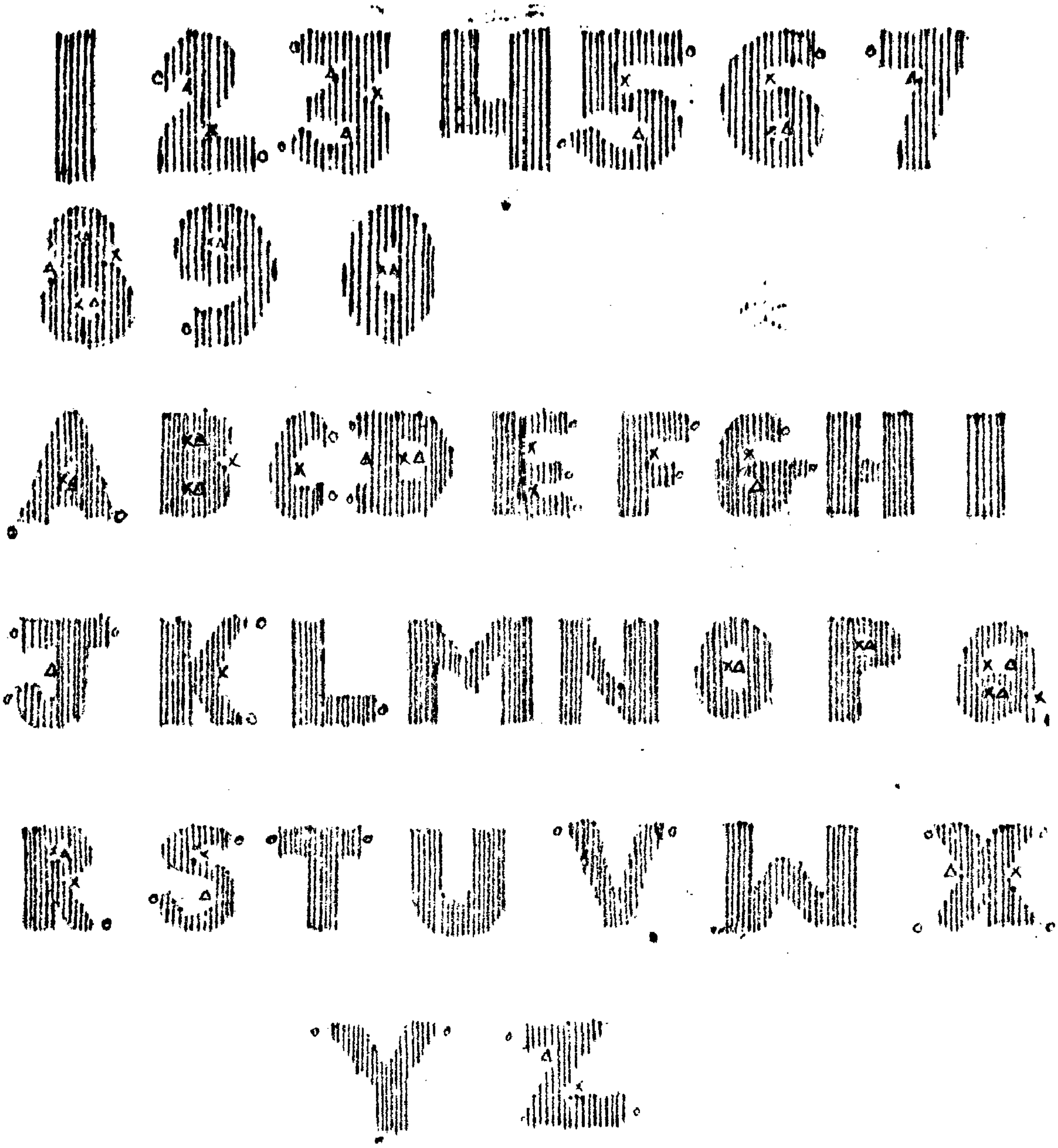


FIG-5.25a Vertical scanning of 26 alphabetic patterns and 10 numerals

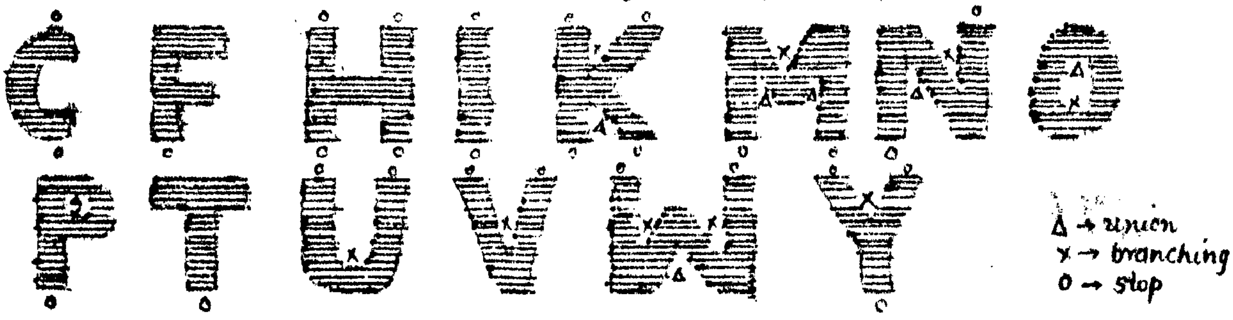


FIG-5.25b Horizontal scanning of some alphabetic letters sets in regard to their relative locations or in regard to the number of features in every feature set.

1) A set of stop points in vertical scanning is denoted by $P_V(s)$ and in Horizontal scanning $P_H(s)$

2) The set of branching points in vertical and horizontal scanning are $P_V(b)$, $P_H(b)$.

3) The set of union points are denoted as $P_V(u)$ and $P_H(u)$ in vertical and horizontal scanning.

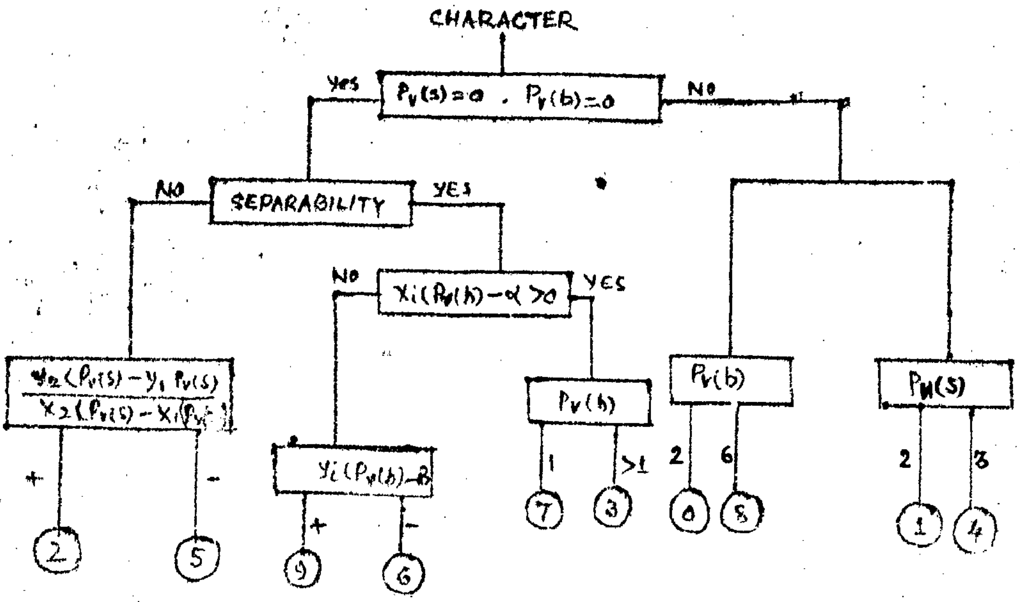
For the characters of numerals printed in accordance with the model or the shape variation is within the class of 'model' set $P_V(u)$ and $P_V(b)$ are represented by one set $= P_V(u) + P_V(b) = P(b)$. Then we have the following properties concerning $P_V(s)$ and $P(b)$ for numerals.

1) $[P_V(s)]$ $[P(b)]$ the number of points in $P_V(s)$ and $P(b)$ is a feature for discriminating some character classes.

2) Two point sets $P_V(s)$ and $P(b)$ are linearly separable for all characters except 2 and 5. There exists a vertical line $x = \alpha$ which separates $P_V(s)$ of characters 3 and 7 on one side and $P(b)$ of the class on the other side. There exists a horizontal line $y = \beta$ which seperate $P_V(s)$ of character 6 on the positive side but the character of 9 on the negative side.

3) For ~~characters~~ character 5 the slope of the line connecting two stop points is positive and that of character 2 is negative. This is shown in table 1 Fig (5-26a)

The recognition of 26 alphabet letters is done using decision table (2). Fig (5-26 b)



Fig(5.26a) Recognition of numerals

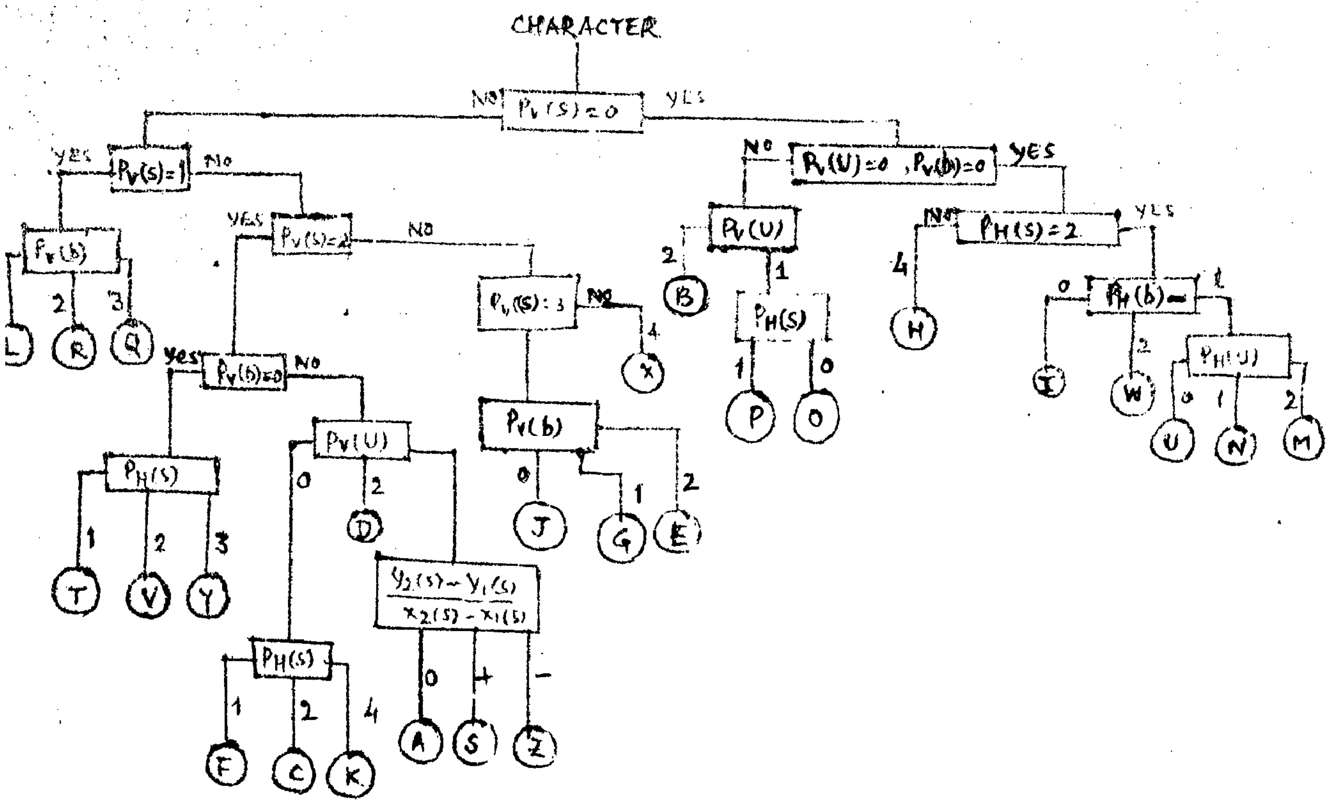


FIG- 5.26 (b) Recognition of 26 alphabetic characters

C H A P T E R - 6

RECOGNITION OF COMPLEX PATTERN THROUGH NONLINEAR METHODS

[14],[15],[17],[18],[19],[20],[22],[24],[27],[28]

In pattern recognition, there are three major problem areas :

1) Description of patterns or extraction of characteristic features from patterns. This is the problem of what to measure

2) Decision procedures - the problem of developing optimum decision procedures for recognition.

3) Adaptation or parameter estimation - when the measurements and recognition system structure are designed, there is generally a set of parameters to be evaluated and optimized. This optimization is data dependent and is usually achieved by some adaptive techniques [25] or statistical estimation.

The usual formulation of the recognition problem is one of the statistical decision. In this formulation recognition procedures can be derived from the functional form of underlying probability distributions. Successive approximations to the probability function lead to a class of recognition procedures. Probability distribution may be approximated by (1) orthogonal expansion (2) product of low order conditional probabilities. Rademacher-Walsh functions are used as the orthogonal basis. A notion of the dependence is introduced to effect the approximation by the product of low order conditional probabilities. The chain dependence and the

2-dimensional neighbour, or mesh, dependence are two instances of tree dependence .

In an abstract sense, we are interested in the choice of the signal space and its coordinate system based upon the pattern classes themselves, it is desirable to have the mathematical structure of orthogonal expansion but the choice of basis should be data dependent to reflect the characteristic properties of the patterns under consideration.

Statistical Recognition

Consider a pattern as a point in signal space (or measurement space), a decision rule is a map from the signal space to the decision space; the decision rule associates a unique decision with each signal. Equivalently, the rule partitions the signal space into disjoint regions and recognition is achieved by ascertaining in which region the signal representing the unknown pattern lies.

Within the framework of statistical decision approach the optimum recognition system depends upon the priori probability distribution of the pattern classes and a set of conditional probability distributions. Let C be the number of classes and ai denote the i^{th} class, Let $p = (p_1, p_2, p_3 \cdot\cdot p_c)$ be the a priori distribution of classes. Each pattern is represented by a measurement vector $x = (x_1, x_2 \ldots x_n)$, n being the number of measurements . Let $P(x/a_i)$ be the conditional probability of a pattern x given that the class ~~s~~ is a_i.

So, the recognition system evaluates for the unknown pattern x, the following set of joint probabilities or their equivalents, of pattern class a_k and pattern x :-

$$P(x,a_k) = p_k\ P(x/a_k) \qquad \dots \quad (1)$$

and then selects the largest one or equivalently one can compute any monotonic function of $P(x,a_k)$, usual one being the logarithm.

so $$\ln P(x,a_k) = \ln p_k + \ln P(x/a_k) \qquad \dots \quad (2)$$

so structure of the recognition system is directly dependent up functional form of the conditional probability $P(x/a_k)$; once the functional form of $P(x/a_k)$ is known the structure of the recognition network can be derived, and the problem of designing the network reduces to the statistical estimation of the unknown parameters of the distribution.

Generally in practice distribution functions are unknown to the designer so the central problem is then to approximate or estimate the unknown distribution. Different approximation lead to different structures of recognition networks. Usually we assume a certain form of probability distribution function $P(x/a_k)$ and common assumptions are independence of measurements of normality. Independence leads to a linear decision procedure and the assumption of multivariate normal distributions leads to a quadratic procedure. First the measurements are converted to binary form and then recognition method is applied. X_i is either 0 or 1.

Linear decision procedure is only a special case of nonlinear one which is more general. A key problem is to decide which nonlinear relations or higher order dependence in the joint probabilities are worth examining and how to weigh them. In the extreme, one could construct a network which requires all 2^n values to represent all the joint events of n binary measurements, which is impractical. So we have to consider structures between this extreme and linear one.

The problem of probability approximation can be considered as the possibility of storing several of the lower order component distributions using the interior of maximum entropy or by using neighbour dependence.[17]

Derivation of Recognition Procedures

The two approaches toward deriving a hierarchy of recognition procedures, are basedupon the methods of approximating the probability obstributions by (1) orthogonal expansion (2) product of low order conditional probabilities.

Statistical Independence

When the measurements within each pattern class are statistically independent, the optimum recognition system is linear. With statistical independence (1) reduces to

$$P(x,a_k) = p_k \sum_{i=1}^{n} P(x_i/a_k) \qquad \ldots (3)$$

and

$$P(x_i/a_k) = [\gamma(i,k)]^{x_i} \, [1-\gamma(i,k)]^{1-x_i} \qquad \ldots (4)$$

$$\text{Hence} \quad \ln P(x,a_k) = \ln p_k + \sum_{i=1}^{n} \ln P(x_i/a_k)$$

$$= b(k) + \sum_{i=1}^{n} w(i,k) \cdot x_i \qquad \ldots (5)$$

where the weights b(k) and w(i,k) are -

$$b(k) = \ln p_k + \sum_{i=1}^{n} \ln \beta(i,k)$$

$$w(i,k) = \ln \left[\frac{\gamma(i,k)}{\beta(i\ k)}\right] \qquad \ldots (6)$$

Where $\beta(i,k)$ and $\gamma(i,k)$ are respectively, the probabilities $P(x_i=o/a_k)$ and $P(x_i=1/a_k)$. Equation (5) is linear in x's. Equation (6) gives a straightforward, non iterative, way of estimating the values of weights based upon samples.

An Orthonormal Expansion

We select a suitable set of orthonormal functions. A set of orthogonal functions which are particularly suitable for binary variables are defined as follows:

Let X denote the set of all points $(x_1, x_2, \ldots x_n)$ with each $x_i = 0$ or 1, X is the set of all 2^n vertices of an n-dimensional cube. Define a set of 2^n polynomials on X as follows -

$$\begin{aligned}
\varphi_1(x) &= 1 \\
\varphi_2(x) &= 2x_1-1 \\
\varphi_2(x) &= 2x_2-1 \\
&\vdots \\
\varphi_n(x) &= 2x_{n-1} \qquad \ldots (7) \\
\varphi_{n-1}(x) &= (2x_1-1)(2x_{2-1}) \\
\varphi_{2^{n-1}}(x) &= \prod_{i=1}^{n} (2x_i-1)
\end{aligned}$$

where $\varphi_j(x)$ for $j>n$ is a finite product of $\varphi_1, \varphi_2, \varphi_n$. This set is an orthonormal basis in the vector space of real valued functions on X with respect to inner product

$$(f,g) = 2^{-n} \sum_{x} f(x).g(x) \qquad \ldots (8)$$

and the norm

$$\|f\| = (f,f)^{1/2} \qquad \ldots (9)$$

consequently any real valued function $f(x)$ on X can be expanded as a unique linear combination of φ's,

$$f(x) = \sum_{i=0}^{2^n-1} c_i \varphi_i(x) \qquad \ldots (10)$$

and the expansion coefficients are

$$c_i = (f,\varphi_i) = 2^{-n} \sum_{x} f(x)\varphi_i(x) \qquad \ldots (11)$$

The set of polynomials as given in (7) is also the orthogonal polynomials associated with the joint probability distribution of n identical, independent and symmetric binary random variables.

Representation of Probability Functions

From the view point of recognition system implementation the direct expansion of the probability distribution is convenient as :

$$P(x/a_k) = \sum_{i=0}^{2^n-1} c_i(k)\varphi_i(x) \qquad \ldots (12)$$

with $$c_i(k) = 2^{n} \sum_{x} \overset{P(x/a_k)}{\cancel{P(xa/k)}}\varphi_i(x) \qquad \ldots (13)$$

An obvious procedure for affecting the approximation is simply to omit higher order terms in (12). For example the first order approximation would just retain the first (n+1) terms in (12):

$$P(x/a_k) \cong \sum_{i=o}^{n} C_i(k)\varphi_i(x)$$ which is linear in x's. The second order approximation would retain the first $1+n+\binom{n}{2}$ terms in (12)

$$P(x/a_k) \cong \sum_{i=o}^{n+\binom{n}{2}} C_i(k)\ \varphi_i(x)$$ which is quadratic in x_i's and so on. More explicitly, coefficients of expansion are $Co(k) = 2^{-n} \sum_x P(x/a_k) = 2^{-n}$ for $1 \leq i \leq n$

$$C_i\ (k) = 2^{-n} \sum_x P(x/a_k)\cdot\varphi_i(x) = 2^{-n}\ [P(x_i=1/a_k)-P(x_i=o/a_k)]$$

and a typical term for $n < i \leq \binom{n}{2}$ is

$$C_{n+1}(k) = 2^{-n} \sum_x P(x/a_k)\varphi_{n+1}(x)$$

$$= 2^{-n}[P(x_1=1,\ x_2=1/a_k)+P(x_1=o,\ x_2=o/a_k)-P(x_1=o,x_2=1/a_k) - P(x_1=1,x_2=o/a_k)] \qquad \ldots (14)$$

In general, the coefficient of j^{th} order term is simply an algebraic sum of the corresponding j^{th}-order joint probabilitics whose sign is determined by the modulo two sum of variables x_i's. For example the coefficient of the first order term say C_1 is evaluated from the marginal probability $P(x_1/a_k)$ and the second order coefficient~~s~~, say C_{n+1} is evaluable from second order probability $P(x,x_2/a_k)$. No higher order probability is required for evaluating any lower order coefficients. There is, however, a serious difficulty in this procedure, the approximation obtained by omitting the higher order terms in (12) may not be a probability distribution at all. The approximation may fail to be non-negative for some x, although the property of unit sum is always satisfied :

Logarithm of Probability Functions:

To avoid this probability of nonnegativeness, we could expand the logarithm of probability instead, provided that $P(x/a_k) > o$ for all x. The expansion is now

$$\ln P(x/a_k) = \sum_{i=o}^{2^n-1} C_i'(k)\varphi_i(x) \quad \ldots (15)$$

and the coefficients are $C_i'(k) = 2^{-n} \sum_{x} \ln P(x/a_k)\varphi_i(x)$ and

$$\ldots (16)$$

The first order or linear approximation then could be

$$\ln P(x/a_k) = \sum_{i=o}^{n} C_i'(k)\varphi_i(x)$$

and the coefficients are $C_o'(k) = 2^{-n} \sum_{x} \ln P(x/a_k)$ and for $1 \leq i \leq$

$$C_i'(k) = 2^{-n} \sum_{\substack{x \\ x_i=o}} \ln(P(x/a_k) - 2^{-n} \sum_{\substack{x \\ x_i=1}} \ln P(x/a_k) \quad \ldots (17)$$

All the coefficients regardless of their order are functions of n^{th} order joint probabilities $P(x_1, x_2, \ldots x_n/a_k)$. In applications, in order to evaluate the lower order coefficients say C_i one has first to estimate the joint probability of the original distribution $P(x_1\ x_2, \ldots, x_n/a_k)$ unless further simplifying assumption is made. Furthermore, the approximation resulted from dropping terms in (15) in general, would not satisfy the property of unit sum, therefore, the normalization is necessary.

Product Expansion

By definition, a joint probability distribution $P(x_1, x_2, x_3 \ldots x_n/a_k)$ can be written as a chain product of conditional probabilities

$$P(x_1, x_2, \ldots x_n/a_k) = P(x_1/a_k)P(x_2/x_1, a_k) \ldots P(x_i/x_{i-1} \ldots x_2, x_1, a_k) \ldots P(x_n/x_{n-1} \ldots x_2 x_1 a_k) \qquad \ldots (18)$$

One way to effect approximation is to impose a limit on the maximum number of variables upon which each variable may be conditioned. In the first order approximation the variables are assumed independent, in the second order approximation, each component probability is conditioned upon at most one of the preceding variables and so on.

Types of dependence are following :

Markov Chain Dependence

A particular type of dependence is that of Markov chain dependence. In the first order chain

$$P(x_i/x_{i-1}, x_{i-2}, \ldots x_2, x_1 a_k) = P(x_i/x_{i-1}, a_k) \qquad \ldots (19)$$

and the joint probability distribution of (18) becomes -

$$P(x/a_k) = \prod_{i=1}^{n} P(x_i/x_{i-1}, a_k) \qquad \ldots (20)$$

with the convention that $P(x_1/x_0, a_k)$ is defined $=$ $P(x_1/a_k)$

Therefore a sequence of successive approximation to $P(x_1, x_2, \ldots x_n/a_k)$ is

$$P_0(x/a_k) = \prod_{i=1}^{n} P(x_i/a_k)$$

$$P_1(x/a_k) = \prod_{i=1}^{n} P(x_i/x_{i-1},a_k)$$

$$P_m(x/a_k) = \prod_{i=1}^{n} P(x_i/x_{i-1},x_{i-2}\ldots x_{i-m},a_k)$$

$$P_{n-1}(x/a_k) = \prod_{i=1}^{n} P(x_i/x_{i-1},x_{i-2}\ldots x_2,x_1,a_k)$$

With a proper convention as to the interpretation of variables with non-positive subscripts. Those variables are to be automatically deleted from the expression e.g.

$$P(x_1/x_0,a_k) = P(x_1/a_k)$$

$$P(x_2/x_1,x_0,x_{-1},a_k) = P(x_2/x_1,a_k) \qquad \ldots (22)$$

In contrast to orthogonal expansion, the present approximation of any order is itself a valid probability distribution i.e. it is non-negative and sums upto unit.

(1) First Order Chain

The basic assumption is that for all i and k (19) is valid, when z_i's are binary, $P(x_i/x_{i-1},a_k)$ can be written as

$$P(x_i/x_{i-1},a_k) = \left\{\beta_0(i,k)\left[\frac{\gamma_0(i,k)}{\beta_0(i,k)}\right]^{x_i}\right\}^{1-x_{i-1}} \times \left\{\beta_1(i,k)\left[\frac{\gamma_1(i,k)}{\beta_1(i,k)}\right]^{x_i}\right\}$$

with the convention that x_0 is always 0. The parameters β's and γ's are the conditional probabilities

$$\gamma_0(i,k) = P(x_i = 1/x_{i-1}=0,a_k)$$

$$\gamma_1(i,k) = P(x_i = 1/x_{i-1}=1,a_k) \qquad \ldots (24)$$

and $\beta_m(i,k) = 1-\gamma_m(i,k)$, $m = 0,1$

$$\text{Then } \ln P(x,a_k) = \ln[p_k \prod_{i=1}^{n} P(x_i/x_{i-1},a_k)]$$

$$= b(k) + \sum_{i=1}^{n} w_1(i,k)x_i + \sum_{i=2}^{n} w_2(i,k)x_i, x_{i-1} \qquad \ldots (25)$$

and the weights are

$$b(k) = \ln p_k + \sum_{i=1}^{n} \ln \beta_o(i,k)$$

$$w_1(i,k) = \ln \left[\frac{\gamma_o(i,k)\beta_1(i+1,k)}{\beta_o(i,k)\beta_o(i+1,k)}\right]$$

$$w_2(i,k) = \ln \left[\frac{\beta_o(i,k)\gamma_1(i,k)}{\gamma_o(i,k)\beta_1(i,k)}\right] \qquad \ldots (26)$$

With the definition that $\beta_1(n+1,k) = \beta_o(n+1,k)$. Because of dependence among x_i's $\ln P(x,a_k)$ is no longer linear in x s. It is quadratic in x's. But due to chain dependence, only n-1, but not all quadratic terms are required. The total number of weights in (25) is $1+n+(n-1) = 2n$

(2) <u>Second Order Chain</u>

In the second order chain expansion each variable is conditioned upon the two preceding variables i.e.

$$P(x_i/x_{i-1},x_{i-2},\ldots x_2,x_1,a_k) = P(x_i/x_{i-1},x_{i-2},a_k) \ldots (27)$$

Each factor in general requires four parameters for specification, they are

$$\gamma_o(i,k) = P(x_i=1/x_{i-1}=0,\ x_{i-2}=0,\ a_k)$$

$$\gamma_1(i,k) = P(x_i=1/x_{i-1}=0,\ x_{i-2}=1,\ a_k)$$

$$\gamma_2(i,k) = P(x_i=1/x_{i-1}=1,\ x_{i-2}=0,\ a_k)$$

$$\gamma_3(i,k) = P(x_i=1/x_i=1/x_{i-1}=1,x_{i-2}=1,\ a_k) \qquad \ldots (28)$$

Let $\beta_m(i,k) = 1-\gamma_m(i,k)$, $m = 0,1,2,3$

Logarithm of the second order chain expansion is

$$T_2(x,a_k) = b(k)+\sum_{i=1}^{n} w_1(i,k)x_i + \sum_{i=2}^{n} w_2(i,k)x_i \cdot x_{i-1}$$

$$+\sum_{i=3}^{n} w_3(i,k)x_i \cdot x_{i-2}+\sum_{i=3}^{n} w_4(i,k)x_i \cdot x_{i-1} \cdot x_{i-2} \quad \ldots (29)$$

and the weights are $b(k) = \ln p_k + \sum_{i=1}^{n} \ln \beta_o(i,k)$

$$w_1(i,k) = \ln \left[\frac{\gamma_o(i,k)\beta_2(i+1,k)\ \beta_1(i+2,k)}{\beta_o(i,k)\beta_o(i+1,k)\ \beta_o(i+2,k)}\right]$$

$$w_2(i,k) = \ln \left[\frac{\gamma_2(i,k)\beta_o(i,k)\ \beta_o(i+1,k)\ \beta_3(i+1,k)}{\beta_2(i,k)\gamma_o(i,k)\ \beta_1(i+1,k)\ \beta_2(i+1,k)}\right]$$

$$w_3\ (i,k) = \ln \left[\frac{\beta_o(i,k)\ \gamma_1(i,k)}{\gamma_o(i,k)\ \beta_1(i,k)}\right]$$

$$w_4(i,k) = \ln \left[\frac{\gamma_o(i,k)\ \beta_1(i,k)\ \beta_2(i,k)\gamma_3(i,k)}{\beta_o(i,k)\ \gamma_1(i,k)\ \gamma_2(i,k)\beta_3(i,k)}\right] \quad \ldots (30)$$

and $\beta_i(n+1,k) = \beta_i(n+2,k) = 0$

This second order chain is cubic in x's.

Tree Dependence

In the first order chain dependence, each variable was conditioned upon immediately preceding variable but here it is that each variable x_i may be conditioned upon any one, not necessarily immediate, of the preceding variables

$$P(x_i/x_{i-1},x_{i-2},\ldots x_2,x_1,a_k)=P(x_i/x_{j(i)}\quad 0\leq j(i)< i,a_k \quad \ldots (31)$$

The index set $\{ j(i)/0 \leq j(i) < i \}$ defines a directed tree, the tree of dependence $j(i)=0$ indicates that x_i is not conditioned. Expansion becomes for tree dependence.

$$T(x,a_k)=\ln [p_k\, P(x/a_k)]=b(k)+\sum_{i=1}^{n} w_1'(i,k)x_i+\sum_{i=2}^{n} w_1''(i,k)x_{j(i)}$$

$$+\sum_{i=2}^{n} w_2(i,k)x_i \cdot x_{j(i)} \qquad \ldots (32)$$

where $b(k) = \ln p_k + \sum_{i=1}^{n} \ln \beta_o(i,k)$

$$w_1'(i,k) = \ln \frac{\gamma_o(i,k)}{\beta_o(i,k)}\ ,\ i=1,2,\ldots n\ ,\ w_1''(j(i),k) = \ln \frac{\beta_1(i,k)}{\beta_o(i,k)}\ ,\ i=2,3\cdots n$$

$$w_2(i,k) = \ln \left[\frac{\beta_o(i,k)\gamma_1(i,k)}{\gamma_o(i,k)\beta_1(i,k)}\right]\ ,\ i = 2,3\ldots n$$

and the basic parameters are

$$\gamma_o(i,k) = P(x_i=1/x_{j(i)} = 0,\ a_k)$$

$$\gamma_1(i,k) = P(x_i=1/x_{j(i)} = 1,\ a_k)$$

$$\beta_m(i,k) = 1-\gamma_m(i,k) \quad \text{for} \quad m = 0,1$$

Similarly higher order chain dependence can be generalized to higher order tree dependence. For example in the second order tree dependence the defining property is

$$P(x_i/x_{i-1},x_{i-2},\ldots x_2,x_1,a_k)= P(x_i/x_{j(i)},x_{h(i)},a_k)$$

where $0 \leq j(i) < i$ and $0 \leq h(i) < i$ the variable x_i is conditioned upon any two (or less), not necessarily the nearest two of the preceding variables $x_1,x_2,\ldots x_{i-1}$. The chain and tree structures are shown graphically in Fig. (6.1).

Network Realization and Estimation of Weights

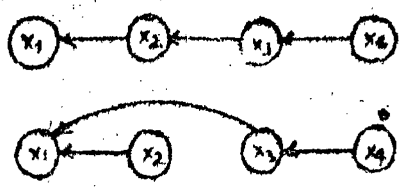
Each approximation to the underlying probability distribution leads to a unique recognition procedure. Network realization is shown in Fig. (6.2).

The first layer receives the binary measurements $x_1, x_2, \ldots x_n$ as input signals and forms products of related measurements. Since the inputs are binary only AND gates are required for multiplication. The outputs of the first layer of AND gates are the required products together with the original inputs $x_1, x_2, \ldots x_n$. They are still binary and feed to the second layer. Second layer consists of a set of weighting and summing networks one for each class of patterns. The weighted sums are $P(x, a_k)$ or $\log P(x, a_k)$. The final layer consists of the usual process of selecting the algebraically largest output of the second layer. The output of the final layer is the recognition decision.

A System for Structure Adaptation

A system which is capable of optimizing the recognition structure is shown in Fig. (6.3). It consists of two subsystems R and E R is the recognition system of variable structure and E has the function of generating and selecting structures and of controlling R.

There are two levels of operation in A. Starting with any initial recognition structure, E generates a set of new structures, each of which is a variation of the starting structure. For each of the generated structures (one at a time)



Chain Structure
$P(X) = P(x_1)\, P(x_2|x_1)\, P(x_3/x_2)\, P(x_4|x_3)$

Tree structure
$P(X) = P(x_1)\, P(x_2|x_1)\, P(x_3|x_1)\, P(x_4|x_3)$

FIG – 6.1

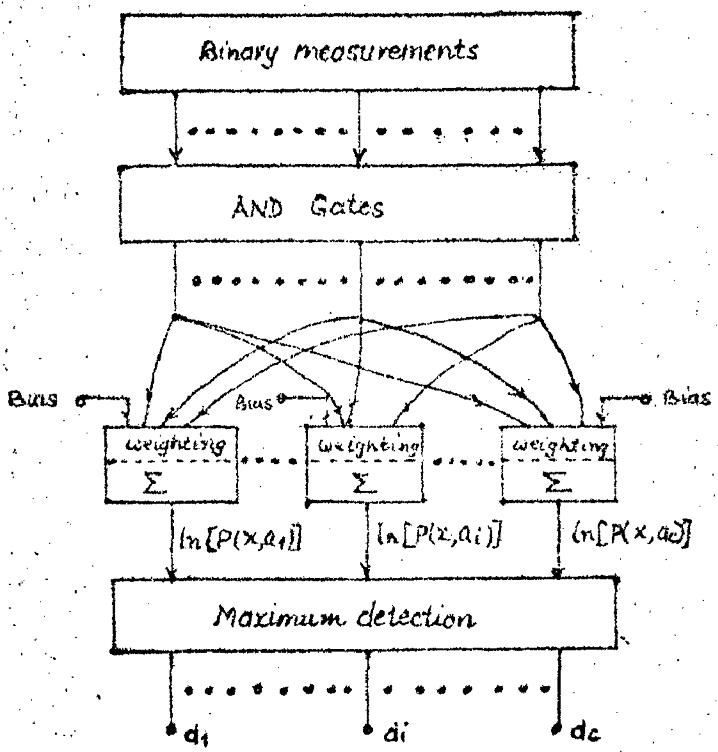


FIG – 6.2 Recognition network for dependent measurements

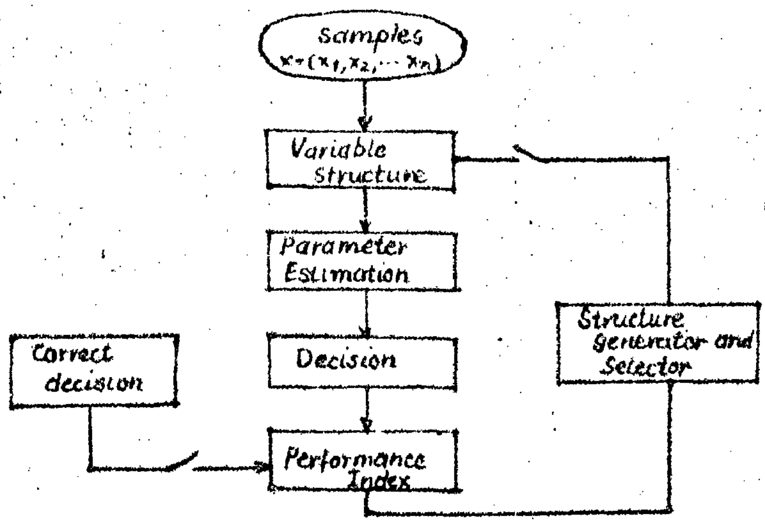


FIG – 6.3 System for structure adaptation

E feeds the structure description to R and recycles the input data or training set. R first adjusts its variable portion to the structure given to it by E, and then estimatesthe recognition parameters based on input data. Having estimated all the parameters, R then proceeds to recognize the input data. A performance index for that particular structure is computed after all inputs have been read. When all the performance indexes forthe set of structures generated by E have been accumulated, E selects the structure with highest performance. E may either terminate this process or generate another set of structures from newly selected structure and repeat the complete evaluation process.

Performance Index

Recognition rate is used here as performance index in evaluating the structures of the recognition network. The performance index is defined in terms of the error rate P(e) as

$$\text{Performance index} = 1 - P(e)$$

as the samples of the design data set are read by a given structure, the recognition results are counted and the recognition rate is calculated.

Another criterion of entropy is used for evaluating structures. The use of either criterion requires approximately the same amount of computation but recognition rate is considered more direct measure of performance.

Structure Adaptation Procedure[25]

The best results will be produced if we explore ~~are~~ all the possible structures in structure adaptation, but it is not feasible practically. Limitations of processing power generally dictate the actual number of structure to be generated and evaluated to be a small fraction of all possible structures. The structures allowed here are restricted to linear, chain and tree structure. The procedure uses a step-by-step optimization technique to attain a local optimum and relies on iterative applications for further improvement. At each step of optimization some heuristic rules are used to~~gether~~ generate limited number of structure variants for subsequent evaluation. Each structure variant differs from given structure by one link.

Three routines are employed for structure adaptation –

LO Routine

This routine finds the first link for a chain structure. Starting from alinear structure, where no measurement relation is considered, the first link of a chain structure is constructed by comparing all $\binom{n}{2}$ 1-link possibilities and selecting the one that minimizes the error rate.

L1-Routine

It determines the permutation of the measurements such that the chain structure corresponding to the measurement ordering is optimal. The input to this routine may be a one-link structure produced by the LO routine, a chain structure or a tree structure. The links in the output chain are constructed one at a time. To add the k^{th} link to the partial chain the best structure is selected from an allowable set of alternative structures. These alternative structures are generated by

(1) Taking one node that is not yet included in the partial chain .

(2) Breaking the link, if any, that originates from this node.

(3) Connecting this node to the end of the partial chain while keeping all other links unaltered.

Following this procedure the routine produces an optimal chain structure i.e. at each step best link is selected.

B-Routine:

It tries to change a chain structure into a tree structure and input to this routine is a chain structure. Starting from the last link in the input chain, each link is broken in succession, each time a link is broken, a set of alternative structures is formed and evaluated by connecting the broken link to one of the nodes in the preceding positions in the chain. Specifically, let $(i_1, i_2, \ldots i_n)$ be the input chain structure. At the $(n-k)^{th}$ step the link between measurements x_{ik} and x_{ik+1} is broken with all other links intact. To form alternative structures x_{ik+1} is linked with x_{ij} successively for every j^{th} less than or equal to k. The best among this set of structures is selected. With new structure, B routine then breaks the link between x_{ik-1} and x_{ik} and repeats the evaluation process until all links in the input chain have been examined and reconnected.

For a set of samples, routine LO is employed first to find the best 1-link structure. This 1-link structure is then used as input to L1 routine. Based on set of samples routine L1 produces achain structure. At this stage of adaptation, we can either go to the B routine directly or use the L1 routine again in an iterative fashion to find a better chain structure before we go the B routine. B routine is used to search for a tree structure with better performance than the chain at hand. This specific approach has been motivated by the fact that composite optimization of chain structures and tree structures imposes a less severe requirement of computing power than a direct search for an optimal tree structure. When the measurements are independent the optimal structure is linear, neither a chain structure nor a tree structure can improve the recognition performance. For this case, the tree structure produced by the procedure will have the same performance as the linear structure.

Example: Let us consider the vertices (x_1, x_2, x_3, x_4) of a four dimensional cube. These 16 vertices will be processed by LO routine among the six 1-link structures denotes by $S_{11}, S_{12} \cdots S_{16}$ in the search tree in Fig. (6.4). Structure S_{15} was chosen Using S_{15} as input structure LT routine generated and evaluated structures S_{21} and S_{22}, S_{21} was selected. Since there was only one more isolated node x_3 at this stage of structure adaptation, a complete chain structure was formed by attaching x_3 to the last node x_1 in the partially formed chain. With this chain structure there was no decision error. This chain was then used as input to L1 routine again to try to att. a better chain structure. No improvement was found. B routine was then used to further reduce the error. The search tree is shown in Fig. (6.5) where the chain structure produced by L1 routine is shown on the top of the search tree. Since there is no guarantee that a new structure will be better than original structure from which it is derived, the original structure is also included in the next comparison. This is seen in Fig. (6.5) where so is relabeled as S_{12} and repeated in the comparison with S_{11} and S_{13} both derived from S_0. For this example, B routine produced the structure S_{21} with no error.

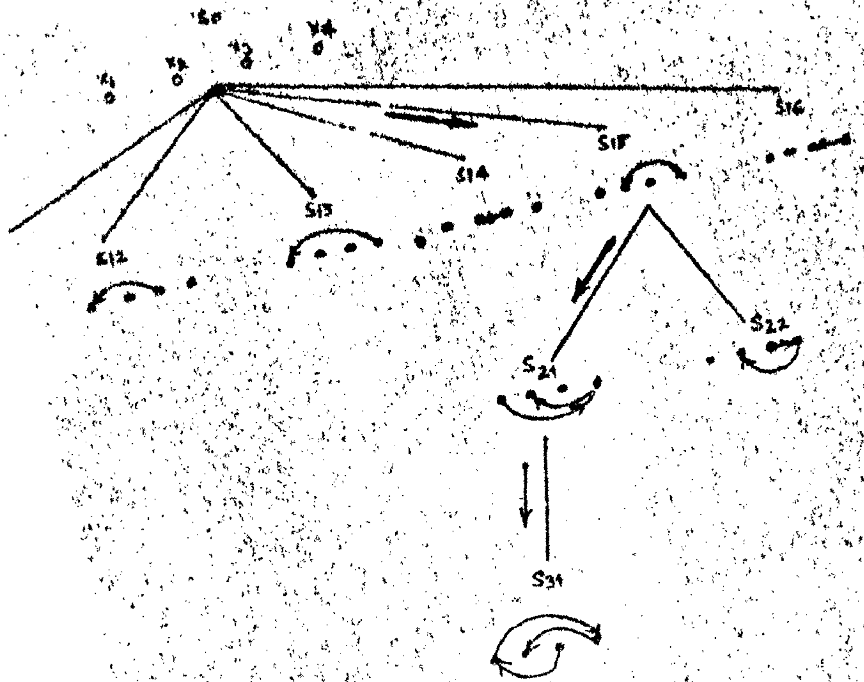
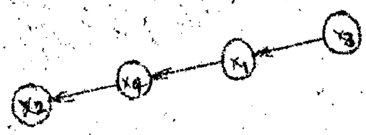


FIG- 6.4 Search for chain structure



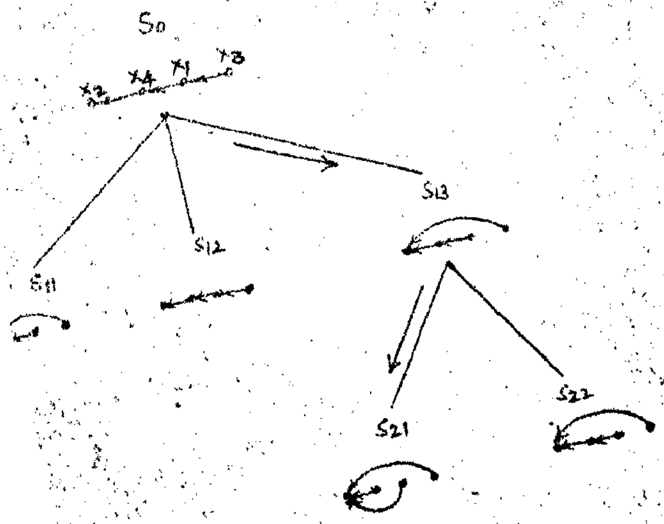
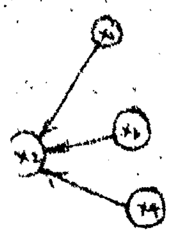


FIG- 6.5 Search for tree structure



CHAPTER - 7

PATTERNS RECOGNITION UNDER REAL WORLD CONDITIONS

Patterns discussed in previous chapters will not be recognized by the methods discussed upto now, if the patterns are enlarged, diminished, lotated, distorted or are in motion or in clutter ~~or~~, unless some mechanism is capable of accommodating these variations of patterns,

Invariance with Respect to Size [2]

Experience shows that recognition is largely independent of the size of the pattern. A line that has a length of 10 foveal cones will be recognized if it is expanded to 200 cones. A possible mechanism that works is obviously starting with a given foveal sensory pattern and repeat the same pattern over and over again at increasing magnification. So a scale factor is used for such enlarged patterns which is adjustable as directed by the pattern stored in memory.

Recognition of Patterns with Different Line Widths

Upto now a pattern with specified line width was detected but if thickness varies then the recognition fails as per previous methods. In variance with respect to the width of this line path can be explained by a repetition of same sensory pattern with varying line thickness.

Recognition of Rotated Patterns[2]

Recognition is independent, within certain limits, of the angular rotation of the patterns. If a human face is tilted 45^{0} or more the brain shows limited capability to ~~re~~-

recognize. In case of patterns with angles and lines, the rotation may place them in another category or the brain recognizes it with a small degree of difficulty in recognition. This invariance can be achieved by mapping from polar to semilog rectangular coordinates. This is shown in Fig. (7.1), for letter K. Fig. (7.1a) shows the letter K as seen by the retina. Retinal fibers are eventually mapped in semilog coordinates as on the right side. Angular distances in the circular field are mapped into horizontal distances in the rectangular field and radial distances in the circular field are mapped into vertical distances using a logarithmic scale in the rectangular field. This completely distorts the original image but it accomplishes three things -

a) Central region of the retina is spread out relative to outer regions, so that the recognition of small objects and details is enhanced.

b) Change in retinal pattern size as in Fig. (7.1b) results in a vertical shift of the rectangular pattern without a corresponding change in the size.

c) Rotation of retinal pattern Fig. (7.1c) results in a horizontal shift of the rectangular pattern without a change in size or orientation.

Patterns in Noisy Background [9]

The recognition of a pattern in noisy field is directed by the first feature selected by attention shift. If it is the feature of the desired pattern, the attention will shift from one feature, to another of the pattern and recognize it

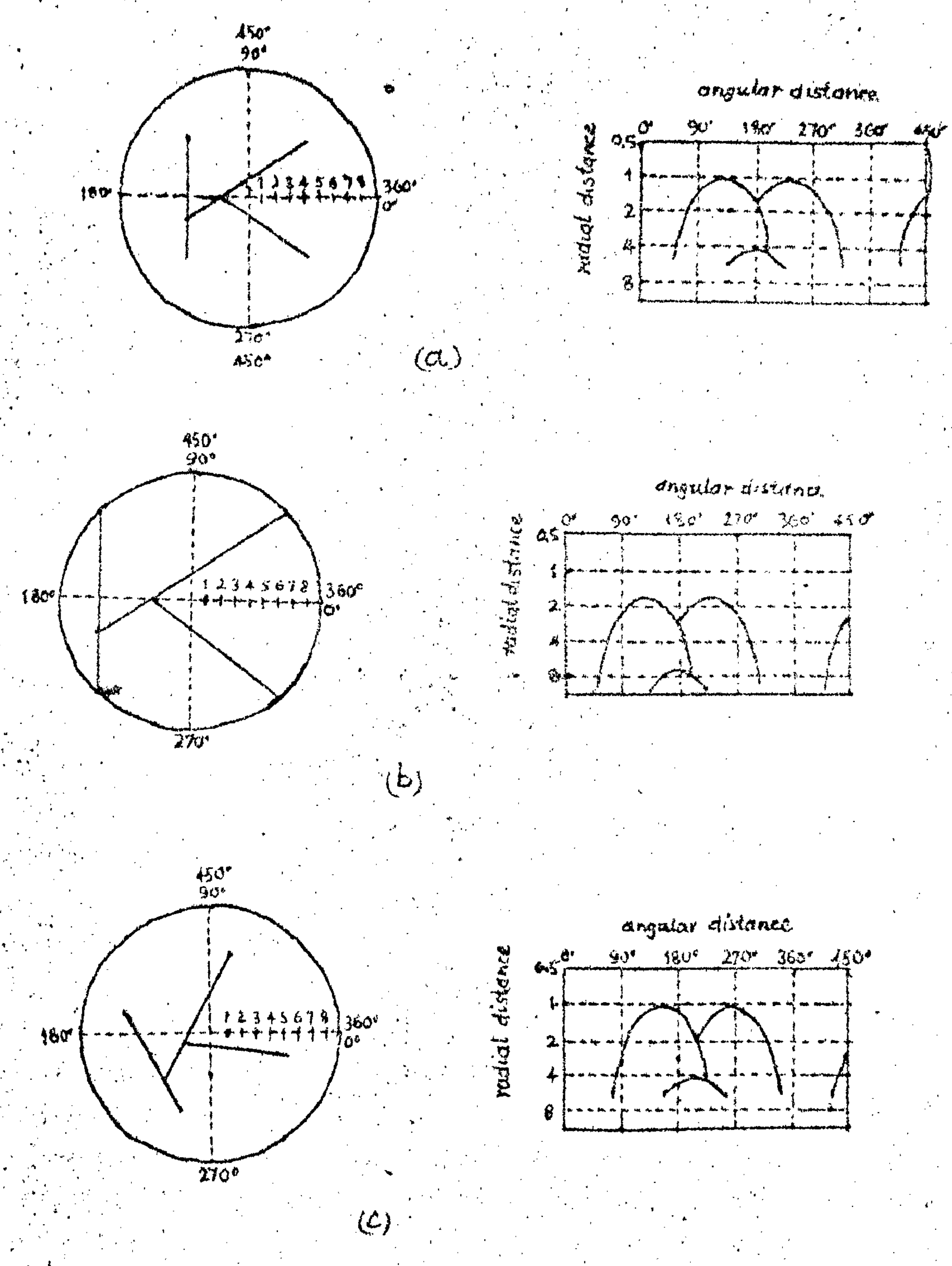


FIG-7.2 Circular pattern on the left is the retinal image of letter K on the right, circular field is mapped in modified polar coordinates. the rectangular field pattern size and orientation remain constant as the original K of(a) is magnified by a factor of 1.5 in (b) or rotated counterclockwise 30° in(c) properly. If the first attention focuses on the feature of noisy background, the recognition will sooner or later, fail and again the process of recognition starts with some other feature. Thus finally, it recognizes the pattern.

Recognition of Moving Patterns [30]

In case of human observers it should be intuitively clear that the motion of an object may itself be recognized as having some contextual significance. For example, if one were to observe an airplane flying backward, one would surely recognize that it was behaving in an improbable manner. Experimentally, it has been determined that a human subject will scan a given pattern with some particular path and this path is a key to the subjects recognition of the pattern. For the recognition of patterns in motion following assumptions are made :-

Assumptions

1) an observed object w will be assumed to be two-dimensional and moving along a straight line of motion tangent to w.

2) the observation of an object w will be assumed to take place at some fixed point of reference r on the line

of the motion during the time that w moves past this point.

3) an observed object w will be assumed rigid i.e. the proper subsets of w from the perspective of observation shall not be in motion with respect to each other. This means that w is considered as only a single object in terms of its motion.

4) an observed object w will be assumed to exist continuously along a line segment extending across it at a right angle to the line of motion i.e. objects are limited to a class whose shapes may be measured as a pair of continuous functions.

5) the observation of an object w will be assumed to measure (a) the length of the line segment extending across w and being a subset of the line which intersects r at right angle to the line of motion, called, 'the size of w at r' and (b) the distance from r to the bottom of that line segment called 'the height of w at r'. Fig. 7.2(a).

Definition (1)

The term f(t) w is defined as an ordered pair of variables as a continuous function over time giving the size and height of w at r.

By assumptions (1) to (5) $f(t)_w$ is the result obtained from observing w. The result will be thought of as a pattern and will be referred to as 'the shape of w'.

<u>Assumption (6)</u>

An observed object w will be assumed to be moving from left to right past r, or exclusively, from right to left past r.

<u>Definition</u> 2

The term $f^*(t)_w$ is defined as the pattern produced by moving w past r in the direction opposite to the direction w moves past r in order to produce pattern $f(t)_w$.

<u>Axiom 1</u>

If the time ordering of either $f(t)_w$ or $f^*(t)_w$ is reversed then, one will have the other pattern. Fig. (7.3).

<u>Assumption</u> 7

An observed object w will be turned around 180°, indicated by the symbol w'.

<u>Axiom 2</u>

If the time ordering of either $f(t)_w$ or $f(t)_{w'}$ is reversed then one will have the other pattern Fig. (7.4).

Theorem - $f(t)_w = f^*(t)_{w'}$,
$f^*(t)_w = f(t)_{w'}$

<u>Definition</u> 3

An observed object w will be said to be moving 'forward' on the pairing of the elements $[f(t), f^*(t)]$ with the subscripts (w,w'). The opposite pairing will then denote w moving 'backward'. Fig. (7.5).

<u>Recognition Algorithms</u>

Three algorithms may be applied to objects in motion depending upon the purpose of algorithm.

(a) The first algorithm is applied for the recognition of a pattern in motion to determine whether or not an observed object w has the same shape as a reference object m in the sense where the shape of an object is something independent of the direction in which the object is moving or facing. If in, this sense, object w has the same shape as object m, then recognition is to occur, otherwise recognition is not to occur.

<u>Algorithm 1</u>

(for recognizing patterns considering shape)

OBSERVE $f(t)_w$

IF $[f(t)_w = f(t)_m]$ GO TO 1 ; ELSE

COMPUTE $f^*(t)_w$

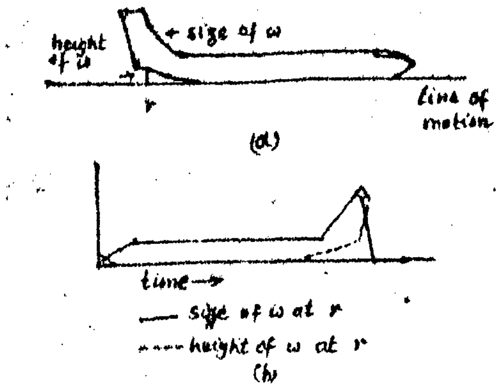
IF $[f^*(t)_w = f(t)_m]$ GO TO 1 ; ELSE

(Nonrecognition)

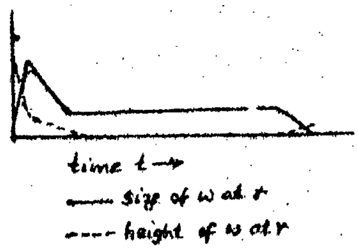
1 STOP (Recognition)

STOP

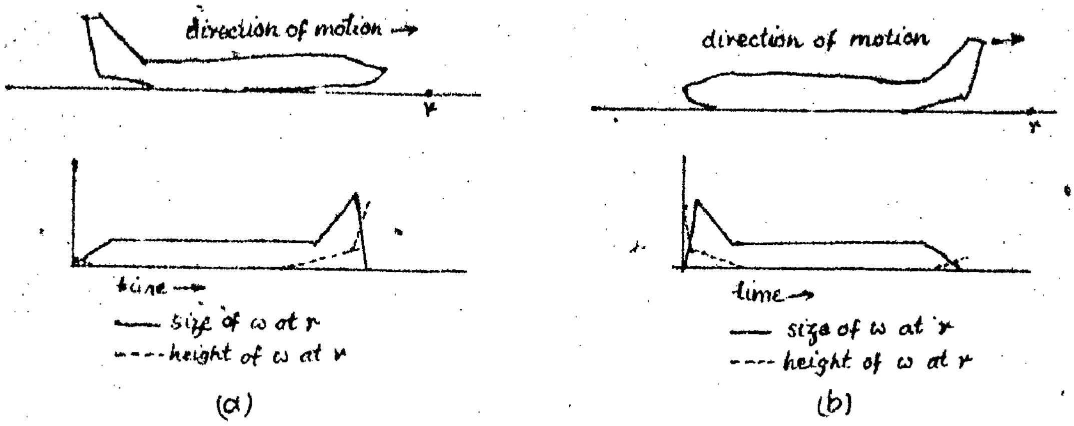
(b) Second algorithm is for recognizing patterns in symbolic context i.e. determination as to whether or not an observed object, w, as a symbol, has the same meaning as does a reference object m. If and only if w, as observed, does have the same symbolic meaning as m, then recognition is to occur. Symbol,



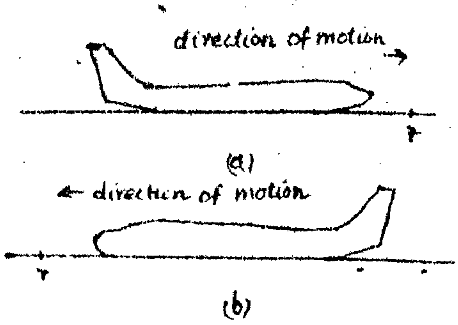
FIG–7.2 (a) features of observed ω from a fixed point r on the line of motion
(b) graph of pair of functions $f(t)\omega$ when (a) is moving from left to right.



FIG–7.3 graph for the case in which pattern of FIG 7.2(a) moves from right to left.



FIG–7.4 (a) object ω and graph for ω moving from left to right
(b) object ω′ and graph for ω′ moving from left to right



FIG–7.5 (a) object ω produces pattern $f(t)\omega$
(b) produces pattern $f^*(t)\omega'$
by theorem two patterns are same
If silhouette is moving forward as opposed to backward then (b) illustrates only other case in which silhouette is moving forward (b) object moving in opposite direction

in ordinary sense is considered as independent of the direction in which symbol is moving. For example, one would want the symbol 7 to mean 'seven' whether it were scanned from left to right or from right to left. However, for symbolic purposes it is necessary to know the direction in which an object is facing since a symbol will not necessarily continue to have the same meaning when it was turned around. For example 7 (seven) turned around becomes Γ (upper case gamma). By theorem, the direction in which an object is facing cannot be determined under the present mode of observation unless the direction in which the object is moving is also determined. By assumption 2, the latter requires that two distinct observations be made of an object w which is to be recognized in symbolic context i.e. w must be observed from two distinct points along the line of motion such that w arrives at either the left hand or right hand point first. Only then it can be determined whether w is moving from left to right or from right to left. Accordingly, let it be assumed for the purpose of second algorithm that two such observations are made resulting in both the time function and a setting for the binary switch $\mu(x)$, where $\mu(x)$ is set to 0 or 1 depending upon the direction in which object x was moving at the time of observation.

<u>Algorithm</u> 2 (for recognizing patterns in symbolic context)

OBSERVE $f(t)_w$, $\mu(w)$

IF $[\mu(w)+\mu(m)\neq 1]$ GO TO 2, ELSE

COMPUTE $f^*(t)_w$

IF $[f^*(t)_w=f(t)_m]$ GO TO 3 , ELSE

1 (non recognition)

STOP

2 IF[$f(t)_w \neq f(t)_m$] GO TO 1, ELSE

3 (Recognition)

STOP

In other words if we and m moves in the same direction when observed, then symbolic recognition must occur only when $f(t)_m$ is equal to $f(t)_w$. But if w and m move in opposite directions when observed, then symbolic recognition must occur only when $f(t)_m$ is equal to $f^*(t)_w$, otherwise w would be recognized as m when w is in fact being observed as m'.

(c) The third algorithm is for recognizing patterns in the context of their motion i.e. determining whether or not an observed object w has the same shape as a reference object m, and additionally, whether or not w is moving in the same manner as m moved when observed, in terms of forward Vs backward. Recognition is to occur if and only if both are true.

<u>Algorithm</u> 3 (for recognizing patterns in the context of their motion)

OBSERVE $f(t)_w$

IF [$f(t)_w = f(t)_m$] GO TO 1 , ELSE

(Non recognition)

STOP

1 (Recognition)

STOP

In other words since $f(t)_w = f^*(t)w'$, algorithm 3 works on the principle that if an object is moving forward as opposed to backward, and is turned around 180^0, then it must begin moving in the opposite direction in order to continue moving forward as opposed to backward.

Speed Independence

A recognition mechanism which was not capable of recognizing an object w independent of the speed with which it moves past r would certainly be of little practical value.

First assume that w moves past r with a uniform nonrelativistic velocity. Then

distance = velocity x time

Then it follows that if an object w is moved past r with velocity v_o to produce pattern $f_o(t)_w$ and is then moved past r with a different velocity v_1 to produce pattern $f_1(t)_w$ then the two patterns will be different even in the case where w moves and faces in the same direction for both observations. This difference results from a scaling of time. If the time scale for $f_o(t)_w$ is T, then the time scale for $F_1(t)_w$ is ET where

$$v_1 = v_o E^{-1}$$

Thus if w is to be recognized independent of the speed component of a uniform velocity with which it moves past r, then the recognition mechanism must generalize the shape of w to accommodate time scaling, ~~to have~~.

CHAPTER - 8

CONCLUSIONS

It is obvious from the previous chapters that it is very difficult and needs a lot of future work to incorporate all the important processes which take place in human visual system for processing and recognition of patterns, simpler as well as complex, and capabilities which account for recognition of patterns under unfavourable real world conditions i.e. rotated, distorted, enlarged or diminished or in noisy background.

The author has applied to concept of short line extractor neuron to the recognition of numerals as well as the 26 letters of the alphabet by a 19 and 30 SLENs arranged in 3 x 5 and 5 x 5 rectangles. The variation in the shape of the letters projected on the SLEN network should not exceed a limit. Secondly, by two stage feature extraction also the numerals as well as letters have been recognized successfully. Through adaptive approach to pattern recognition complex patterns can be tried. There had been some very serious difficulties in the organization of this dissertation:

(1) Very small work has been done in this field and a large portion of the work done for pattern processing and recognition does not take into consideration physiological facts available for human brain.

(2) The mathematical models suggested by different researchers for the recognition of handprinted numerals letters signatures, or faces etc. grow so much complicated that it looks unfeasible for the brain to accomodate them keeping in view the limitations imposed by total number of neurons required for such bulky calculations and storing them for future reference. In considering these mathematical models to trace a feature of any pattern which the brain can do with not much effort and immediately, we have to do so much mathematical juggling that sometimes even computer takes hours of operation.

(3) Correlation of brain, while visual aspects of patterns with other sensory function as audition speech, smell, touch, taste and thoughts etc. throws light on those gaps which are to be deeply interpreted while studying human brain as a whole. It defies our depth of knowledge.

The models discussed in this work for recognition of colour, simple pattern and complex patterns reasonably well perform that function but the requirement is of a single theory to unify them.

REFERENCES

1. Russell Myles Decoursey, 'The Human Organism', Third Edition, 1968 McGraw-Hill Book Company, New York.

2. Sid Deutsch, 'Models of Nervous System', 1967 John Wiley and Sons Inc. New York.

3. G.F.Inbar, 'Signal Analysis and Pattern Recognition in Biomedical Engineering,' Proceedings of International Symposium Held in Haifa July 9-11,1974, 1975 Ed. John Wiley and Sons, New York.

4. S.N.Levine, 'Advances in Biomedical Engineering and Medical Physics, Vol. 2, 1968, John Wiley and Sons Inc. p 243.

5. G.Biernson and A.W.Snyder, 'A model of Vision Employing Optical Mode Patterns for Color Discrimination', IEEE Trans. Systems Science and Cybernetics Vol. SSC-4, No.2 July 1968 p 173.

6. G.Biernson, 'Spectral Scanning as a Mechanism of Color Vision', IRE Trans. on Military Electronics, Vol.MIL 7 No. 2&3, April-July 1963, p 103.

7. K.Fukushima, 'Visual Feature Extraction by a Multilayered Network of Analog Threshold Elements', IEEE Trans. on Systems, Science and Cybernetics Vol. SSC-5 No. 4 Oct. 1969, p 322.

8. K.S.Fu, P.J.Min. and T.J.Li, 'Feature Selection in Pattern Recognition' IEEE Trans on System, Science and Cybernetics, Vol. SSC-6, No.1, January 1970, p 33.

9. D.Noton, 'A Theory of Visual Pattern Perception', IEEE Trans. on Systems Science and Cybernetics Vol. SSC-6, No. 4 , October 1970, p 349.

10. A.D.Allen and D.Noton, 'Comments on 'A Theory of Visual Pattern Perception', IEEE Trans. on Systems Man and Cybernetics, Vol. SMC-1 No.4, October 1971, p 388.

11. M.B.Herscher and T.P.Kelley, 'Functional Electronic Model of Frog Retina', IRE Trans, on Military Electronics, Vol. MIL-7, No. 2 and 3, April-July 1963, p 98.

12. S.Deutsch, 'Conjectures on Mammation Neuron Networks for Visual Pattern Recognition', IEEE Trans. on Systems Science and Cybernetics, Vol. SSC-2, No.2, Dec. 1966,p-81.

13. P.C.Chuang, 'Recognition of Handprinted Numerals by Two-Stage Feature Extraction', IEEE Trans. on System, Science and Cybernetics, Vol SSC-6, No. 2 April 1970, p 153.

14. C.K.Chow and C.L.Liu, 'An approach to Structure Adaptation in Pattern R$_e$cognition', IEEE Trans on Systems Science and Cybernetics Vol SSC-2, No.2, December 1966, p 73.

15. C.K.Chow, 'A Class of Non-linear Recognition Procedure', IEEE Trans on Systems,Science and Cybernetics Vol. SSC-2, No. 2 December 1966, p 101.

16. P.M.Lewis, 'The Characteristic Selection Problem in Recognition Systems', IRE Trans. on Information Theory Vol. I T-8 Feb. 1962, p 171.

17. C.K.Chow, 'A Recognition Method Using Neighbour Dependence', IRE Trans. on Electronic Computers, Vol. EC-11, October 1962, p 683.

18. G.Nagy, 'Feature Extraction on Binary Patterns, 'IEEE Trans on Systems Science and Cybernetics Vol. SSC-5 No. 4, October 1969, p 273.

19. E.M.Riseman, 'Logical Networks for Feature Extraction', IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-1, No. 1, January 1971, p 43.

20. D.J.Quarmby and J.Rastall, 'Experiments on Hand Written Numeral Classification', IEEE Trans. on Systems Man and Cybernetics, Vol. SMC-1. No.4, October 1971, p 331.

21. H.Marko, 'A Biological Approach to Pattern Recognition', IEEE Trans. on Systems, Man, and Cybernetics Vol. SMC-4, No. 1, January 1974, p 34.

22. T.Takagi, 'Experiments of Pattern Discriminating System Using Neural Cell Models', IEEE Trans on Systems, Man, and Cybernetics, Vol. SMC-5, No.2, March 1975, p 276.

23. G.J.Kaufman, Jr. and K.J.Breeding, 'The Automatic Recognition of Human Faces from Profile Silhouettes,',
IEEE Trans. on Systems, Man, and Cybernetics, Vol. SMC-6, No.2, Feb. 1976, p 113.

24. G.A.N.Preston, 'The Good Gestalt Concept in Machine Perception', IEEE Trans. on Systems, Man, and Cybernetics, Vol. SMC-6, No.5, May 1976, p 367.

25. James S.Bryan, 'Experiments in Adaptive Pattern Recognition', IRE Trans. on Military Electronics', Vol.MIL-7, No.2 and 3, April-July 1963, p 174.

26. J.Sklansky, 'Image Segmentation and Feature, Extraction', IEEE Trans. on Systems, Man, and Cybernetics, Vol. SMC-8, No.4, April 1978, p 237.

27. A.I.Torsoff, 'Man-Machine Considerations in Automatic Handprint Recognition, IEEE. Trans. on Systems, Man, and Cybernetics, Vol. SMC-8, No.4, April 1978, p 279.

28. J.Yacuk, 'Alphabetic Handprint Reading, ' IEEE Trans on Systems, Man, and Cybernetics, Vol. SMC-8, No.4, April 1978, p 279.

29. M.Briot, M.Ronand, and J.Stojiljkovic, 'An approach to Spacial Pattern Recognition of Solid Objects', IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-8, No. 9 Sept. 1978, p 690.

30. A-D.Allen, 'Patterns in Motion', IEEE Trans. on Systems, Man and Cybernetics, Vol. SMC-2, No.-1, January 1972, p-93.

31. J.Y.Lettvin, H.R.Maturane, W.S. Mcculloch and W.H.Pitts, 'What the Frog's eye Tells the Frog's Brain', Proc.IRE Vol. 47, November 1959, p 1940.