Computer Vision based Intelligent Techniques for Hand Gesture Recognition

THESIS

Submitted in partial fulfillment
of the requirements for the degree of
DOCTOR OF PHILOSOPHY

By

Ankit Chaudhary

Under the Supervision of

Dr. -Ing. J. L. Raheja

BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE
PILANI (RAJASTHAN) INDIA

March 2012

BIRLA INSTITUTE OF TECHNOLOGY AND SCIENCE PILANI (RAJASTHAN) INDIA

CERTIFICATE

This is to certify that the thesis entitled "**Computer Vision based Intelligent Techniques for Hand Gesture Recognition**" submitted by **Mr. Ankit Chaudhary** ID No. **2009PHXF437P** for the award of Ph.D. degree of the Institute embodies original work done by him under my supervision.

Date: Signature of the Supervisor

Head Machine Vision Lab
Scientist F
Digital Systems Group
Central Electronics Engineering Research Institute
Council of Scientific and Industrial Research
Pilani-333031, Rajasthan, INDIA

"If we knew what it was we were doing, it would not be called research, would it?"

-Albert Einstein

Acknowledgement

I am indebted to many people who have provided me support and encouragement during the course of my research.

In the first place, I would like to express my gratitude whole-heartedly to my supervisor Dr. Ing. Jagdish Lal Raheja, Head, Machine Vision Lab, CEERI/CSIR Pilani for his excellent supervision, valuable advice, suggestions and guidance from the very early stages of this research. I would like to thank him for the extraordinary experiences that I had throughout the work. Besides providing me unflinching encouragement and support in various ways, he has also allowed me the freedom to experiment with my innovation which has in a major proportion enhanced and nourished my intellectual growth.

I am immensely thankful to Prof. B.N. Jain, Vice-Chancellor, BITS Pilani for providing me this opportunity to pursue the on-campus PhD of the Institute. I express my gratitude to Prof. S.K. Verma, Dean, Academic Research Division (ARD), BITS Pilani and all ARD staff for their constant official support, encouragement and making the organization of my research work through the past few years easy.

I thank my Doctoral Advisory Committee (DAC) members, Dr. M.K. Rohil and Dr. R.K. Gupta, who spared their valuable time to go through my draft thesis and were audience to my pre-submission seminar in order to provide several valuable suggestions that immensely helped in improving the quality of my PhD thesis report.

A special word of appreciation is owed to Prof. Navneet Goyal, Head, Dept. of Computer Science for providing the necessary aid, support and facilities on several occasions. I acknowledge his promptness in providing me with all the equipment to facilitate the research.

Thanks to Prof. G. Raghurama, Director, BITS Pilani, Pilani Campus and Dr. Chandra Shekhar, Director, CEERI/CSIR Pilani for their constant support and concern. I would like to gratefully acknowledge Prof. J. P. Misra, Chief IPC Unit, Prof. S. Mohan, Dean, Admissions, Prof. Shan. B., Dean, ARP and many others for their indispensable help and for creating a pleasant research atmosphere.

Words fail me to express my gratitude to Prof. Rahul Banerjee, Chief SDET Unit and Prof. Praveen Ranjan Srivastava for their direction and motivation. Collective and individual acknowledgements are due to all my fellow researchers in BITS and CEERI who have directly or indirectly helped me in my work. Many thanks to Mr. P. Vyas, Mr. D.K. Tyagi and all my friends who were always ready to lend a hand.

I thank everybody who was important to the successful realization of this thesis, as well as express my apology that I could not mention personally one by one.

Finally and most importantly I would like to thank my wife for her unconditional love and support. She has always believed in me and has encouraged me to give my best.

Ankit Chaudhary

Abstract

In the last few decades hand gesture recognition has been considered to be an easy and natural technique for human-machine interaction. Many applications have been developed and enhanced based on hand gesture recognition. These applications range from mobile phones to advanced robotics and from gaming to medical science. In most of the existing commercial and research applications, recognition of hand gestures has been performed by employing sensor-based wired embedded gloves or by using vision-based techniques where colors, chemicals or paperclips are used on the hand. However, it is desirable to have hand gesture recognition techniques that are applicable to a natural and bare hand, which is normally used for depicting gestures in verbal communication. Another important issue involved in vision-based techniques is their variance to light conditions. As the light conditions change, the threshold used for the segmentation also has to be changed. Bare hand gesture based applications where no external device or color is used, do not work for different light intensities. In case of human skin, different user’s skin color appears different in the same light intensity while same user's skin color varies in different light conditions.

This work is aimed at light invariant bare hand gesture recognition when there is no restriction on the hand gesture. The preprocessing is performed by developing an image cropping algorithm where only the region of interest is included in the segmented image. The segmented image is compared with a predefined gesture set which are required to be installed in the recognition system. These images are stored and feature vectors are extracted from them. These feature vectors are presented using an orientation histogram which provides a view of the edges in the form of frequency. There by if two same gestures are shown in different light intensities, they mapped to same gesture in stored data. The mapping of the segmented image orientation histogram is firstly done using the Euclidian distance method. Secondly, the supervised neural network is trained for the same and better recognition results are shown to be obtained.

An approach to control an electro-mechanical robotic hand using hand gesture is also presented in this thesis. Such a robotic hand has applications in commercial, military or emergency operations where human life cannot be risked. For such applications, an artificial robotic hand is required to perform real-time operations. This robotic hand should move fingers in the same manner as a human hand. For this hand geometry parameters are obtained in 2D using webcam and also using MS KINECT. The parameter detection is direction invariant in both methods. Once the hand parameters are obtained, the fingers angle information is obtained by performing a geometrical analysis. An artificial neural network is also implemented for angles calculation. These two methods provide information about only one hand, either right or left. A separate method that is applicable to both hands simultaneously is also discussed and fingers angles are calculated. Finally, a conclusion has been drawn from the observations and from the results of hand gesture recognition and angle calculation that this research work can be used to remotely control a robotic hand using hand gestures. Also the developed system is able to recognize hand gestures in different light conditions.

Table of Contents

List of Figures

List of Tables

List of Acronyms

ANN	Artificial Neural Network
BLOB	Biggest Linked Objects
COP	Centre of Palm
CCF	Concentric Circular Filter
CSF	Circular Separability Filter
DOF	Degree of Freedom
FSM	Finite State Machine
HCI	Human Computer Interface
HMI	Human Machine Interface
HG	Hand Gesture
HGP	Hand Geometry Parameters
HGR	Hand Gesture Recognition
OH	Orientation Histogram
PIM	Pictorial Information System
ROI	Region of Interest
SVM	Support Vector Machine
TGR	Trajectory Guided Recognition

Chapter 1

Introduction

"Vision is the best gift given to us by the creator out of all our strengths and features. The way of seeing an object and recognizing it seems very easy from human point of view but if you want a machine to do the same then it is probably the most complex task on the earth! Interested Researchers are trying to do the same since 40 years but still no machine exist which can recognize any object without ambiguity". [Graham 1991]

As computers are becoming increasingly pervasive, there is a growing interest in the development of new approaches and technologies for bridging the human-computer barrier. The aim is to bring human computer interaction (HCI) to a regime where the interactions with computers become as natural as the interactions between humans. As a part of HCI, incorporating hand gestures into communication methods is an important research area. Hand gesture recognition (HGR) is the natural way of human machine interaction. Today many researchers in the academia and industry are studying different techniques that make such interactions easier, natural and convenient without the requirement for any additional devices.

Gesture Recognition Systems offer to the machine the ability to identify, recognize and interpret human emotions through gestures. Gesture identification is a natural way to pass emotional signals to the machine, as a human expresses his/her feelings most often through gestures. Generally defined as any meaningful body motion, gestures play a central role in everyday communication and often convey emotional information about the gesticulating person.

This thesis is particularly focused on identifying hand gestures in natural condition. Techniques for preprocessing and segmentation of the original image, and hand image interpretation are also considered in this thesis.

1.1 Hand Gesture Recognition

Though the research has presented advancements in gesture recognition, further advancements are required for making the gesture recognition process more accurate. The existing research on gesture recognition can be classified into three categories. The first category is the glove based analysis. This employs sensors attached to a glove that transduce finger flexions into electrical signals for determining the hand posture. This system requires the user to wear a cumbersome device and carry a load of cables that connect the device to a computer. This hinders the ease and naturalness with which a user can interact with a computer controlled environment. Potentially, the awkwardness in using gloves and other devices can be overcome by video-based noncontact interaction techniques identifying gestures.

The second category comprises of the models based on gesture images. Many statistical, probabilistic and other models have been proposed. One of the techniques in this approach involves building a three-dimensional model of a hand. This model is matched to the hand by one or more cameras and parameters corresponding to the palm orientation and joint angles are estimated. These parameters are used to perform corresponding gesture classification. Additionally, in order to initialize the parameters the user places the hand in a specified position. The parameters can also be manually instantiated.

The third category involves the analysis of drawing gestures. This method usually involves stylus, which is used as an input device. This method also leads to the recognition of written text. Majority of the work on hand gesture recognition has employed mechanical sensing, most often direct manipulation for the virtual environment and occasionally for symbolic communication. Sensing the hand posture mechanically involves a range of problems including reliability, accuracy and electromagnetic noise. Visual sensing has the potential to make gestural interaction more practical, but potentially embodies some of the most difficult problems in machine vision. This is because, the hand is a non-rigid object and even worse self-occlusion is commonly encountered.

1.1.1 Gesture Recognition Process

Live input of images can be taken using any normal web camera. As a video is a sequence of images, the image sequence would be processed one by one. An image frame may contain many undesired objects in addition to the hand gesture under consideration. To identify the gesture correctly, the part of the image depicting the hand needs to be separated from the part composed of the undesired objects. To separate the skin from the image, a commonly used method involves applying a suitable skin filter with an experimentally obtained threshold. This results in the separation of the skin from the image while the undesired parts of the image can be removed. In image processing, like other fields, the results are not extremely sharp when preprocessing is performed. There can be noise in the image as the falsely detected skin pixels and also the detected portion can have jagged edges. Noise removal and smoothing operations need to be applied to the image in order to get only the region of interest (ROI) with smooth edges in the resultant images.

After obtaining ROI, the gesture can be classified using many known techniques. If there is a known set of gestures which could occur in the image, then ROI has to be compared with the collected data. This can be done by storing the gestures and extracting features from them into a database. Consequently, the test image feature vector would be compared against it. Many researchers have also used soft computing techniques for the same purpose.

Many vision based applications have used fingertips to track or manipulate gestures. This will help in understanding the hand position in the image. Another hand geometry parameter is the centre of palm (COP). If the COP and the fingertips are known, the clarity of the hand gesture in the image can be significantly enhanced.

1.1.2 Research Gaps

Hand gestures can be classified into two categories: static and dynamic. A static gesture is a particular hand configuration or pose that is represented by a single image, while a dynamic gesture can be considered as a continuous motion of the hand. The static gesture has only one type of a gesture, while the dynamic gesture can contain more than one gesture during a particular period of time. Gesture recognition from video sequences or an interactive input is one of the most important challenges in real time for researchers working in the area of computer vision and image understanding. It is very complex to perform a required operation on an arbitrary image. One needs to extract the ROI, which makes the work faster and reduces the computational complexity. However, image processing algorithms involve an old and known problem of incremental time. A technique that involves a smaller number of computations is required in order to reduce the time involved in the initial processing.

The skin color in the images varies in different light intensities. The same skin color may seem different when the light intensity changes. Moreover, if different users employ the system, then their skin colors are quite likely to be different. The system needs to detect the ROI for all types of skin colors. This is still a major issue when it comes to installing applications in the public domain. A light intensity invariant system is needed so that performed gesture could be identified successfully.

Open fingers' detection is a known process in vision techniques, which provides accurate results. However, closed finger detection does not provide accurate results. Many methods do not consider the closed finger in the gesture or they count it wrongly. Limited research has been performed in the area of bended fingers' angle calculation using vision based methods. This area need to be investigated in depth. This area helps mimic the hand operations virtually or on hardware devices.

1.1.3 Applications

The geometry of the hand is complex and it is hence hard to construct it in a virtual environment. However, the functionality and the degree of freedom of the hand encourage researchers to develop a hand-like instrument. During the last few decades, researchers have been interested in automatically recognizing human gestures for several applications, namely sign language recognition, socially assistive robotics, directional indication through pointing, control through gestures, alternative computer interfaces, immersive game technology, virtual controllers, affective computing and remote controlled robots. Mobile companies are trying to make handsets which can recognize gestures and hence operate over short distances [Kroeker 2010][Tarrataca & Santos+ 2009]. Pickering [Pickering 2005] wrote that initially touch-based gesture interfaces would be popular, while non-contact gesture recognition technologies would be more attractive finally and this is reality today. Recently human gesture recognition catches the peak attention of the research in both software and hardware environments. Hand gesture with a single hand can be very worthy in case of giving command to the computer or to a robotic system [Shimizu & Yoshizuka+ 2006]. However, in most practical cases, both hands are involved. Therefore, taking into account both hands is also a challenge.

1.2 Thesis Organization

This thesis is targeted to change the current way of developing vision-based applications bringing the natural computing in the picture. The user should be able to naturally use vision-based systems as they behave with other humans. The block diagram showing the chapter-wise work flow is shown in the Figure 1.1. Chapter 1 discusses problem description and research gaps the area of hand gesture recognition and possible application domain. Chapter 2 states the proposed goals for this research work. Chapter 3 presents the current state of art with focus on soft computing and other intelligent techniques. Several issues are discussed in the existing scientific literature on hand gesture recognition. These will help us to find out new ways to solve research issues.

Chapter 4 discusses the preprocessing of captured images using webcam & KINECT. Consequently, the ROI is obtained. Here, a novel technique of ROI cropping is introduced for fast processing. The hand gesture recognition and light invariant results are demonstrated in Chapter 5. The Orientation histogram technique was used for gesture matching. Hand geometry parameters detection, which gives fingertips and centre of palm positions, is presented in Chapter 6. These parameters are needed to gather information about the hand position in the image frame. Chapter 7 presents the single hand fingers' angle calculation methods using geometrical analysis and neural network while Chapter 8 presents the angle calculations if both hands are employed for depicting gestures. This method also calculates the angles while the fingers are bent. Finally, the conclusions and future work are discussed in Chapter 9.

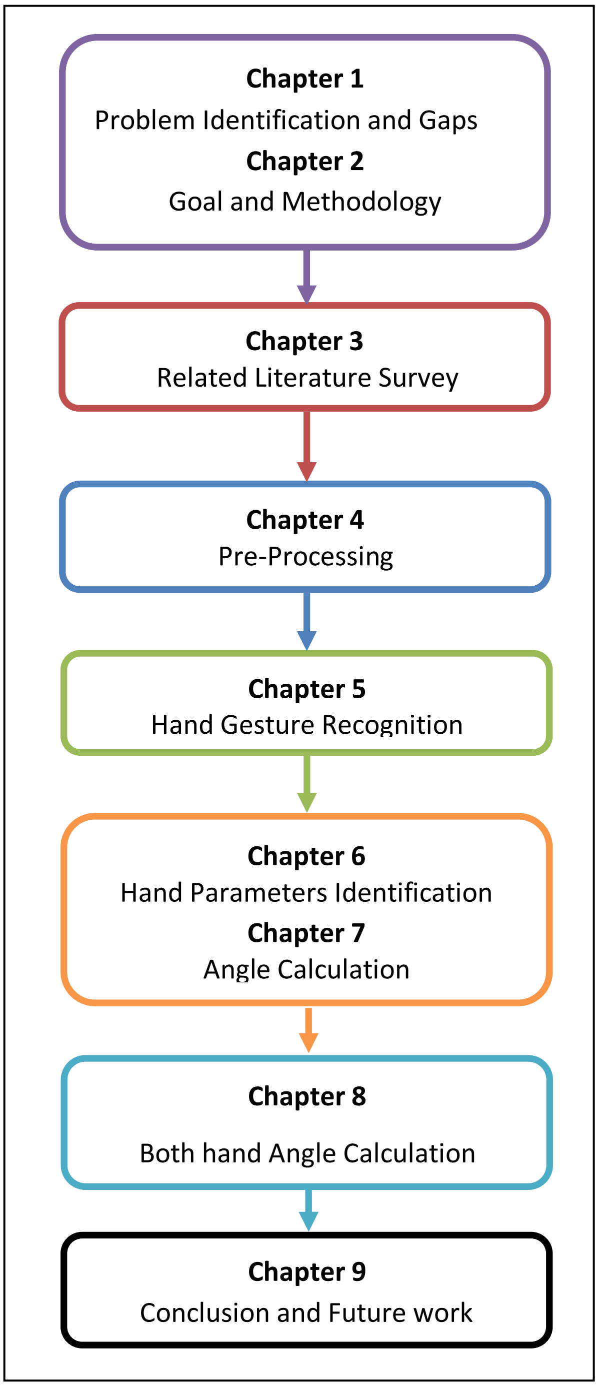


Figure 1.1: Chapter-wise work flow.

Chapter 2

Scientific Goals

The next step is to set scientific/ research goals so that the research direction should be clearly defined. After careful consideration of problem statement from Chapter 1 and with the help of known techniques in the area of computer vision, we set following goals for this thesis:

1. **Improve the state of the art of hand gesture recognition using enhanced intelligent methods-** Current techniques in hand gesture are using external devices/colors/chemicals. The objective is to develop vision based techniques, using them natural hand gesture recognition would be possible.

2. **Investigate a faster method to reduce image preprocessing algorithm time-** Image processing algorithms have known problem of incremental computational time. Also, captured image frames are always bigger than region of interest. This leads to unnecessary computation of non ROI part. If only ROI would process to all operations, the computational time will decrease by a big fraction.

3. **Investigate a direction invariant method to detect hand gesture in real time-** As discussed in research gaps in Chapter 1, it is necessary for natural hand recognition system to recognize hand gesture irrespective of hand direction. User should not be forced to show hand in a particular direction to camera. As the proposed system is supposed to work in daily life applications, it should do operations in real time.

4. **Investigate a light intensity invariant method to detect hand gesture in real time-** Skin color changes its appearance respective of light intensity. Also different users have different skin color. So a threshold would work for a particular light intensity for one user. To make system more robust, so that any person can use it and in any visible light, a real time light invariant hand gesture recognition method is needed.

5. **Explore automated techniques to calculate angles of bending fingers from hand gesture-** As discussed in the applications section in chapter 1, a robotic hand can be controlled using human gesture. The open finger detection is a well known technique today, but in case of closed fingers, detection rate is very poor. Also, there is no work on fingers' angles information like how much fingers are bent. To control robotic hand via human hand, the bent fingers' angles are needed to find out from the live input.

After goal setting, we need to define a work sequence in which the proposed research would be done. Figure 2.1 shows a sequence of research steps, which will be followed in this thesis. First of all, scientific literature survey would be performed based on research goal and latest techniques implemented in literature would be discussed. The experimental work will start after this. The pre-processing would be done on live images taken using webcam and ROI would be extracted. The hand gesture recognition would be performed using intelligent techniques applied on ROI.

The hand geometry parameters are needed for hand shape information. These will be detected from ROI and it would help in further fingers' angle calculation. As user is free to show either one or both hand, the finger angle detection should be able to work for both conditions.

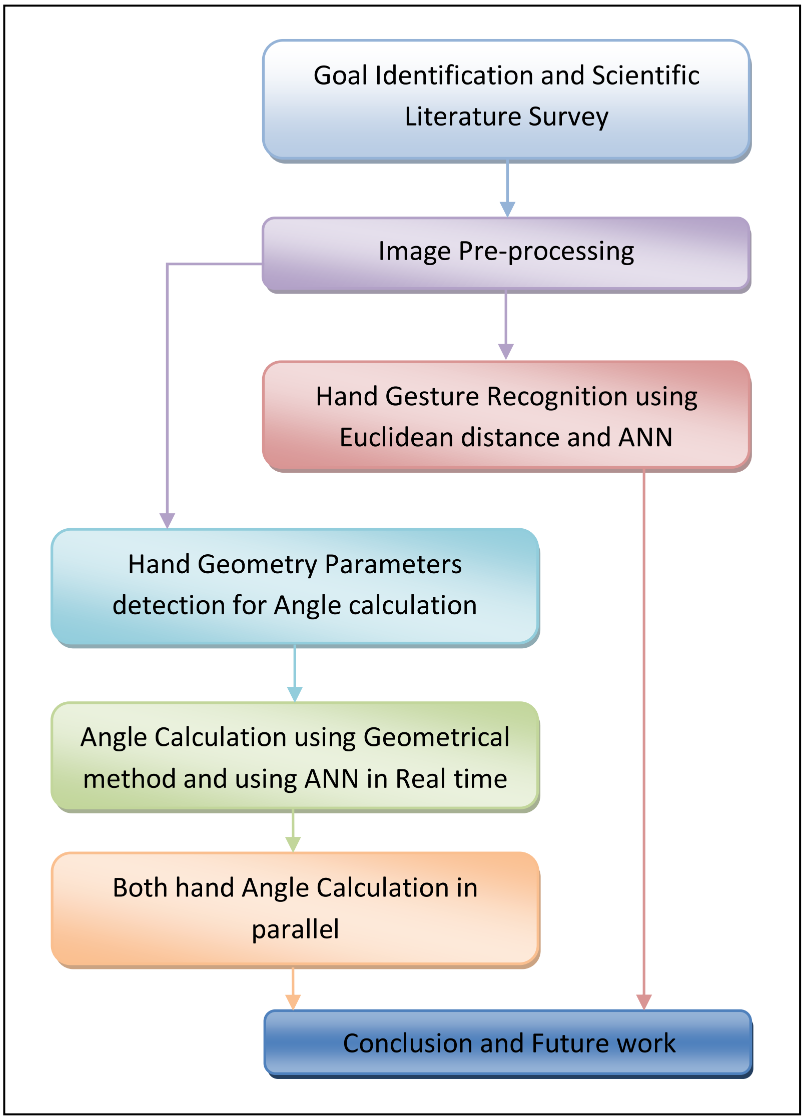


Figure 2.1: Steps in Research Work.

Chapter 3

State of the Art

This chapter provides a brief overview of the state-of-the-art methods and results related to hand gesture recognition techniques. These methods are used for comparison and as a stepping stone for next chapters. Here different methods for hand gesture recognition are presented and discuss the major problems in this area which are addressed in this thesis. We also anticipate results based on proposed solutions discussed in later chapters and put them into their frame to reference here.

Hand gestures (HG) recognition is one of the major areas of research for the engineers, scientists and bioinformatics to interpret the human behavior in different scenarios. HG based interaction with machines is a natural technique for communication which people follow in their general lives. Today many researchers in the academia and industry are studying various applications for making HG based interactions more easy, natural and convenient without wearing any extra devices. HG has applications that range from games control to computer vision enabled robot control, from virtual reality to smart home systems, from security systems to training systems and to many other areas.

Gesture recognition is a sub-field of vision and image understanding that helps in interpreting an image or sequence of images i.e. video into a meaningful description. In this chapter the state of art in the area of hand gesture recognition is discussed with focus on the intelligent approaches including soft computing based methods like artificial neural network, fuzzy logic, genetic algorithms etc. The methods involved in the preprocessing of an image for segmentation of region of interest and hand image construction are also studied. Most researchers have used fingertips for hand detection in appearance based modeling. In this chapter various applications are described which are focused on fingertip detection based methods. Finally, a comparative study of results presented in various research studies is presented.

3.1 Natural Hand Gesture Recognition

The natural gesture research community has identified the fundamental types of natural HG recognition techniques. Natural HG communication is a very active research area in the field of Computer Vision. Such a communication technique provides the ease to interact with machines without the requirement of any extra device. Moreover, if the users do not have sufficient technical knowledge about the system, they are still able to use the system with their bare hands. When communicating, humans often express their statements through gestures. The gestures are depicted naturally with the words and the gestures help enhance the understanding (of the communication) of the listener. Gestures allow individuals to communicate feelings and thoughts with different emotions with words or without words [Kendon 2004]. A human gesture can be any but few have a special meaning.

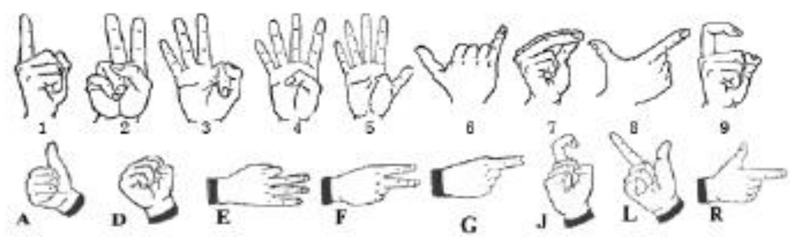


Figure 3.1: Chinese Sign Language [Zhang & Lin+ 2009].

A human hand can move in any direction and can bend at any angle in all available vector spaces. Chinese sign language as shown in Figure 3.1, uses hand gestures to represents digits as well as alphabets. In the past many researchers [Sturman & Zeltzer 1994][Pavlovic & Sharma+ 1997][Cho & Kim+ 1999][Huang & Pavlovic 1995][Quek 1994] [Wang & Cannon 1993] have tried with different instruments and equipment to measure hand movements like gloves, sensors or wires. However, in these techniques a user has to wear the device, which is highly impractical. This deficiency in previous studies motivates the investigation of a technique involving contactless gesture recognition. Such a technique, which provides a natural human to human interaction, provides a new research dimension in the area of computer vision.

According to Mitra [Mitra & Acharya 2007] gesture recognition is a process where a user makes a gesture and a receiver recognizes it. Using such a technique, an easy interact with machines is possible and can convey to them a particular message based on the environment and application syntax. Even people who cannot communicate orally (i.e. sick, old or young child) would also benefit from this technology. Researchers are working to develop such HG based systems for handicapped people. On the commercial side, mobile companies are trying to make handsets which are able to recognize gestures naturally and could operate over small distances [Kroeker 2010][Tarrataca & Santos+ 2009]. The focus of this thesis is on human to machine interaction (HMI), in which a machine is able to recognize the gesture depicted by a human. There are two types of approaches for HG recognition that are found in literature. These are:

a. Appearance based approaches in which a hand image is reconstructed using the image properties and extraction.
b. Model based approaches in which different models for the images are employed and consequently the images are represented on the computer.

Here the approaches are classified based on the method used for HGR. Many approaches have been developed to interact with machines using glove based systems [Baudel & Lafon+ 1993][Sturman & Zeltzer 1994] to neural networks [Nolker & Ritter 2000]. Users always prefer an easily implementable and natural technology in HMI and hence prefer technologies that interpret visual inputs [Pavlovic & Sharma+ 1997]. Fels [Fels & Hinton 1993] implemented a multilayer neural network to transform hand gestures into audio output using gloves. Pickering stated [Pickering 2005] that even though initially touch based gesture interfaces would be popular, ultimately, non-contact gesture recognition technologies would be in demand. Input to a machine using a gesture is simple and convenient. However, the implementation of such a system involves a number of difficulties as Xu [Xu & Zhu 2009] states "The human hand is a complex deformable object and gesture itself has many characteristics, such as diversities, ambiguities, temporal and spatial differences and human vision itself is an ill-posed problem".

Pickering [Pickering 2005] describes a real time gesture based driving system simulator developed at Carnegie Mellon University with the help of General Motors. Many researchers [Do & Jung+ 2006][Premaratne & Nguyen 2007][Kohler 1996][Bretzner & Laptev+ 2001][Sawah & Joslin+ 2007][Kim & Fellner 2004] have also used a color strip or a full sleeved shirt to detect a hand image in captured images. A detailed survey on gesture recognition is presented in [Mitra & Acharya 2007][Pavlovic & Sharma+ 1997][Ong & Ranganath 2005]. Gesture segmentation is a part of the gesture recognition process, which has been reviewed in [Xu & Zhu 2009] and [Mahmoudi & Parviz 2006] based on color spaces.

Choi [Choi & Ko+ 2001] brings the attention of researchers to an old problem, namely the incrementing processing time of algorithm's complexity. Choi says that "the most important issue in field of the gesture recognition is the simplification of algorithm and the reduction of processing time". He uses a morphological operation to implement his system using the center points extracted from primitive elements by morphological shape decomposition. Lu [Lu & Shark+ 2009], Gastaldi [Gastaldi & Pareschi+ 2005] and Ozer [Ozer & Lu+ 2005] use a parallel approach in the design and implementation of their system. Different threads are implemented in such a manner that they can run in parallel and can compute faster.

Shin [Shin & Tsap+ 2004] presented a 3D HG based system that has application in fruit fly chromosomes based on 2D slices of CT scan images. Lee [Lee & Lee+ 2004] shows that a system that he developed for remote control systems is also implementable in motion recognition. He uses 3D systems with two or more cameras to detect commands issued by a hand. Villani [Villani & Heisler+ 2007] has attempted to develop a system for teaching mathematics to the deaf with an easy user interface. Morimoto [Morimoto & Miyajima+ 2007] presents an interesting virtual system in which he pushes virtual buttons using fingers in the air and recognizes it by employing 3D sensors.

3.2 Hand Detection Approaches

A number of techniques are presented in literature for detecting a hand gesture in the acquired image after preprocessing. As discussed previously, these approaches are classified into two categories, namely the appearance based approaches and the model based approaches. In this section, a detailed discussion as well as a literature review of the two approaches is presented.

3.2.1 Appearance Based Approaches

These are the approaches in which the image is considered as a scene in the processing. In these approaches different types of noise could affect the preprocessing result. In the spatial domain the light intensity and background of an object play an important role. Many applications are [Nolker & Ritter 2002][Verma & Dev 2009] [Nguyen & Pham+ 2009][Shin & Tsap+ 2004][Lee & Park 2009][Zhou & Ruan 2006][Gastaldi & Pareschi+ 2005][El-Sawah & Joslin+ 2007][Kim & Fellner 2004][Lee & Chun 2009][Lien & Huang 1998] based on fingertip detection for the hand image construction. In the spatial domain, which is the focus of this research, the fingertip is detected and consequently the hand position is defined.

Nolker [Nolker & Ritter 2002] focuses on a large number of 3D hand postures in her system called GREFIT. She uses finger tips in the hands as the natural determinant of a hand posture to reconstruct the image. The gray scale images of size 192x144 are processed. In her system she suggests a few approaches to locate the fingertip in a hand, namely

1. Color fingertips and make a histogram
2. Use different templates or images of a prototype

Verma [Verma & Dev 2009] has extracted the features from the image that are comprised of fingertips, edges and generate vectors for 2D modeling. He uses the Harris corner detector to extract fingertips corresponding to corners. Nguyen [Nguyen & Pham+ 2009] uses gray scale morphology and geometric calculations to relocate the fingertip locations using learning based model on a 640x480 pixel size frame. Nguyen uses an approach that is similar to that used by Shin [Shin & Tsap+ 2004] to detect both hands by considering the skin color. To identify the hands, Nguyen [Nguyen & Pham+ 2009] uses a skin segmentation technique based on the Gaussian model. The density function of the skin color distribution is given by

$$\mathrm{Prob}(\mathrm{c}|\mathrm{skin}) = \sum_{i=1}^{k} \pi_i \, p_i(\mathrm{c}|\mathrm{skin}) \tag{3.1}$$

where k is the number of components and π_i is the weight factor of the i^{th} component. He uses CIELUV color space to represent skin and interestingly he uses the palm to finger length ratio to construct the hand image. Zhou [Zhou & Ruan 2006] works with 320x240 size 24 bit image frames. Zhou uses the Markov Random Field to remove the noise component in the processed image.

Gastaldi [Gastaldi & Pareschi+ 2005] obtains the hand perimeter using Gaussian filters and Freeman's algorithm [Freeman 1961] to localize fingertips in the image for 3D detection. Kim [Kim & Fellner 2004] tries to recognize gesture in a dark room on black projection for his system. Although the system is vision based, he used florescent white paper to mark finger tips in the captured image. This is not practical for generic purposes since the user has to wear white florescent strips.

Kim uses the Kalman filter for finding fingertips and their correct positions in a recursive manner. Stefan [Stefan & Athitsos+ 2008] implements a system which can detect the motion of fingers in the air visually. Such a system is used to recognize the numbers from 0 to 9 for command transfer. Ng [Ng & Ranganath 2002] develops a system to recognize the fourteen predefined gestures in 320x240 pixel sizes in 24 bit color, where hands are moving and the system is able to work with one or both hands. Ng performs a wrist cutting operation on hand images to make both images invariable.

3.2.2 Model Based Approaches

In these approaches different models can be constructed to get a result in other forms which can be used to get the relevant image part later. These models are inspired from machine learning or the frequency domain. El-Sawah [El-Sawah & Joslin+ 2007] uses histograms for calculating the probability for skin color observation. Hu [Hu &

Yu+ 2000] takes the Gaussian distribution for background pixels marking. He then subtracts the pixels from the new image to acquire the gesture image as defined in (3.2). Lee [Lee & Lee+ 2004] uses the same technique to get the hand gesture image.

$$\Delta = |I_n - B| \tag{3.2}$$

In the modeling of his application of human activity monitoring, Hu [Hu & Yu+ 2000] applies Genetic Algorithm (GA) to chromosome pool with P_{c0} and P_{m0} as crossover and mutation rate respectively which he found using different statistic attributes. Crossover creates new chromosomes while mutation in this case introduces new genes into chromosome. Lee [Lee & Chun 2009] uses the YC_bC_r skin color model to detect the hand region and then he applies the distance transform. Tarrataca [Tarrataca & Santos+ 2009] uses the RGB and HSI color space model based algorithm for skin detection. Malassiotis [Malassiotis & Strintzis 2008] develops a system to recognize real time hand gestures in German sign language in 3D using a sensor enabled camera which can recognize the pattern based on illumination and computes the 3D coordinates of each point on the surface. The details about the pattern finding 3D coordinates are discussed in [Tsalakanidou & Forster+ 2005].

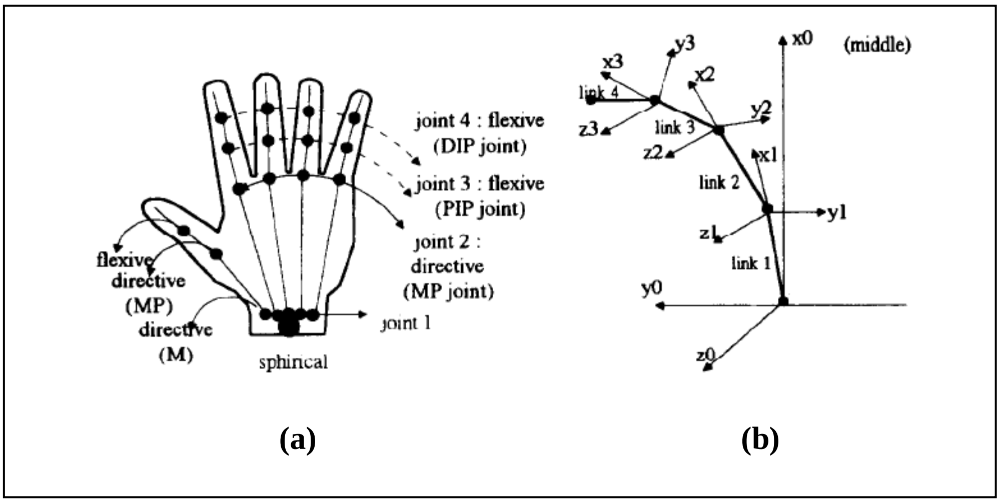


Figure 3.2: Hand Geometry Mapping (a) Hand model (b) Local coordinate frames on the joint position for middle finger [Lien & Huang 1998].

Lien [Lien & Huang 1998] presents a model based system for HGR where the joints in fingers have one degree of freedom (DOF), effective joins have 2 DOF and spherical joints have 3 DOF. Hence, all fingers have 4 DOF while the thumb has 5.

He then defines the local coordinate system with the origin located at the joints as shown in Figure 3.2. This system is interdependent on the fingers movement. He uses the fast fitting method to determine the angle imposed by each finger.

3.3 Soft Computing Approaches

Under the umbrella of soft computing some of the principal constituents are Neural Networks, Fuzzy Systems, Machine Learning, Evolutionary Computation, Probabilistic Reasoning and their hybrid approaches. In this chapter the focus is on mainly three components, which are applied to a wide range of applications. These are:

a. Artificial Neural Networks
b. Fuzzy Logic
c. Genetic Algorithm

3.3.1 Artificial Neural Network

An Artificial Neural Network (ANN) is composed of a number of highly interconnected processing elements (called Neurons) which operate together in to solve specific problems [Sivanandam & Deepa 2007]. ANN can be configured for solving problems like pattern recognition or data mining through learning based models. ANN also has capabilities like adaptive learning, self-organizing and real time operations using special hardware.

Nolker [Nolker & Ritter 2002] uses an ANN based layered approach to detect fingertips. The fingertip vectors are obtained and are transformed into finger joint angles to an articulated hand model. For each finger a separate network is trained on the same feature vectors. The input to each network is a vector of size 35, while the output is only two dimensional. Lee [Lee & Park 2009] uses the Hidden Markov Model (HMM) for gesture recognition using shape features. Gesture state is determined after stabilizing the image component as open fingers in consecutive frames. He also used the maxima and minima approach like Raheja [Raheja &

Shyam+ 2010] for constructing the hand image and Finite State Machines like Verma [Verma & Dev 2009] for gesture finalization.

Wang [Wang & Mori 2009] proposed an optical flow based powerful approach for human action recognition using learning models. In this optical flow approach, the hidden parts in the image are also labeled. This max-margin based algorithm can be applied to gesture recognition. In his system Kim [Kim & Fellner 2004] uses a learning model for dynamic gesture recognition. Huang [Huang & Hu+ 2010] uses HMM and RNNs for gesture classification from the collected vectors of hand pose frames. Outputs of both the classifiers are combined to get better results and it was input to the developed GUI. He used Fourier descriptors to represent the boundary of extracted binary hand and trained Radial Basis Function consisted of 56 input nodes, 38 hidden layer and five output nodes. The activation function of the j^{th} hidden node is given by (3.3).

$$\varphi_j(x) = \exp\left(-\frac{||x-c_j||^2}{2\sigma_j^2}\right) \tag{3.3}$$

where x is the input vector, c_j is the center and σ_j is the spread of $\varphi_j(x)$. Just [Just & Marcel 2009] presents a comparative study of HMM and IOHMM HG recognition technique on the two openly accessible databases and it is concluded that HMM is a better choice for HG recognition modeling.

Stergiopoulou [Stergiopoulou & Papamarkos 2009] uses an unsupervised self-growing and self-organized Neural Gas network for 31 pre-specified gestures. Although he makes several assumptions, namely the arm should be vertical and the user employs only his right hand while the system is not applicable to left-handed users. The raised fingers detection in the hand is performed by finding the fingertip neuron, which is followed by the other neurons chain as shown in Figure 3.3.

The center of the palm can be calculated by employing the gravity method from the neuron only in the palm area and the distance from the fingertips to the palm center is calculated. However, the main problem in gesture recognition is that only the raised fingers can be counted in the presented algorithm (as shown in Figure 3.3(e)) and gesture is recognized accordingly. Then he applied a likelihood classification to obtain the gestures that are predefined based on the raised fingers.

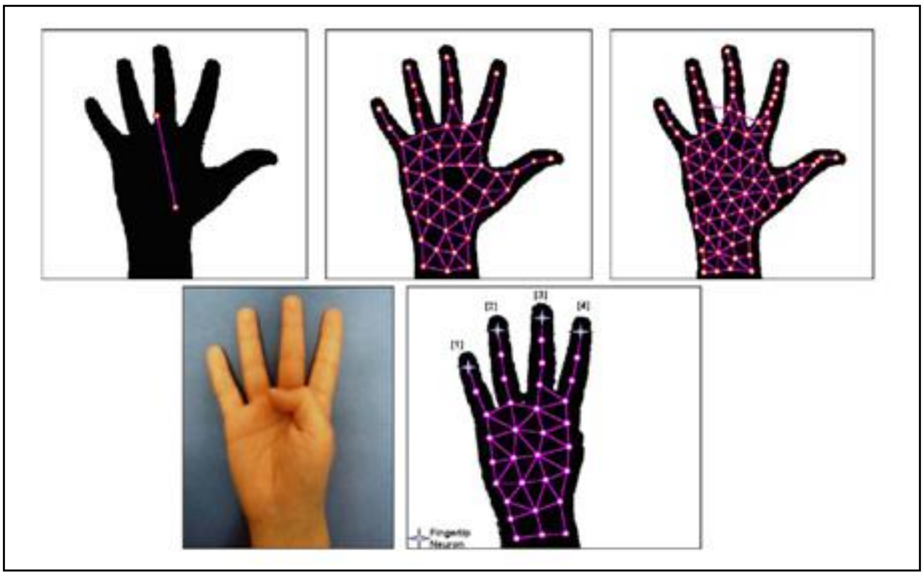


Figure 3.3: SGONG network working (a) Start with two points (b) Growing stage with 45 neurons (c) Output with 83 neurons (d) Hand gesture (e) Only raised fingers would be counted [Stergiopoulou & Papamarkos 2009].

3.3.2 Fuzzy Logic Based Approaches

In the 60s, Lotfi Zadeh [Zadeh 1965] presented fuzzy logic in an innovative way. His view was that for precise processing, accurate information is not necessary, it can be performed if imprecise data is available. It is more realistic than a computer obtained binary result. As described in [Sivanandam & Deepa 2007] "Fuzzy logic is a multi-valued logic that allows intermediate values to be defined between conventional evaluations". Verma [Verma & Dev 2009] uses c-mean fuzzy clustering based finite state machines (FSM) to recognize hand gestures. The formula for centroid calculation of fuzzy c-means clusters states that the centroid is the mean of all points weighted by their degree of belongings to the cluster center. Hence, for each point x and a coefficient $u_k(x)$ that gives the degree in the k^{th} cluster, the mean (i.e. centre$_k$) is given by [WIKIa].

$$centre_k = \frac{\sum_x u_x(x)^m x}{\sum_x u_x(x)^m} \tag{3.4}$$

where x_k is the k^{th} trajectory point.

In second phase these clusters map onto FSM states and the final state shows gesture recognition. However, Verma [Verma & Dev 2009] did not implement it. Schlomer

[Schlomer & Poppinga+ 2008] uses k-mean algorithm on clusters and then applies HMM and Bayes-classifier on vector data. Trivino [Trivino & Bailador 2007] tried to make a more descriptive system which can convert human gesture positions into a linguistic description using fuzzy logic. He related it to natural language processing (NLP). He used sensors and took only few positions into consideration, namely the sitting and standing positions.

3.3.3 Genetic Algorithm Based Approaches

Genetic Algorithm originates from the field of biology, but it also has wide applications in optimization performed in computational sciences. This method is very effective when obtaining optimal or sub-optimal solutions to problems as it has only few constraints [Sivanandam & Deepa 2007]. It uses generate and test mechanism over a set of probable solutions (called as population in GA) and provides an optimal and acceptable solution. It executes its three basic operations (i.e. reproduction, crossover and mutation) iteratively on the population.

El-Sawah [El-Sawah & Joslin+ 2007] focuses on a very generic scenario where he uses a generic non-restricted environment, generic not-specific application for gesture recognition using genetic programming. He uses crossover for noise removal in gesture recognition, Dynamic Bayesian Network (DBN) for gesture segmentation and perform gesture recognition with fuzzification. Hu [Hu & Yu+ 2000] applies the Genetic Algorithm on his system to make a 2D parametric model with human silhouette in his application of Human Activity Monitoring. The best quality of GA is that it operates in parallel at different points, hence performing faster computations.

3.3.4 Other Approaches

There are many other intelligent approaches for hand gesture recognition. Raheja [Raheja & Shyam+ 2010] proposes a new methodology for real time robot control using Principal Component Analysis (PCA) for gesture extraction and pattern recognition with saved images of 60x80 image pixels formats in a database. He uses syntax of a few gestures and determines the corresponding actions of the robot. He claims that the PCA method is significantly faster than the neural network based methods which require training databases and a greater computational power.

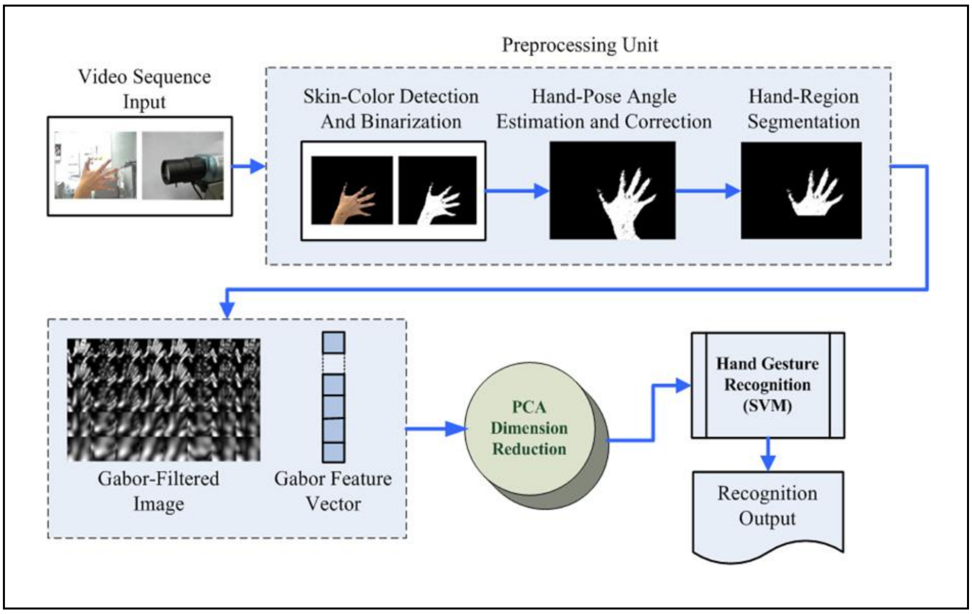


Figure 3.4: Hand Gesture Recognition process form video [Huang & Hu+ 2010].

Huang [Huang & Hu+ 2010] uses PCA for dimensionality reduction and Support Vector Machnies for gesture classification in using skin color model switching for varying illumination environment. In Huang's approach (see Figure 3.4) image sequences are sent for skin-color detection, hand pose angle estimation and hand region segmentation. Then the resultant images are divided into forty 20x20 pixels and are run through the Gabor filter. Morimoto [Morimoto & Miyajima+ 2007] also uses PCA and maxima methods. Gastaldi [Gastaldi & Pareschi+ 2005] uses PCA to compress five image sequences into one and get Eigen vectors and Eigen values for each gesture. He uses statistical HMM model for gesture recognition. Lee [Lee & Kim 1999] also used HMM with threshold model for predefined gesture recognition.

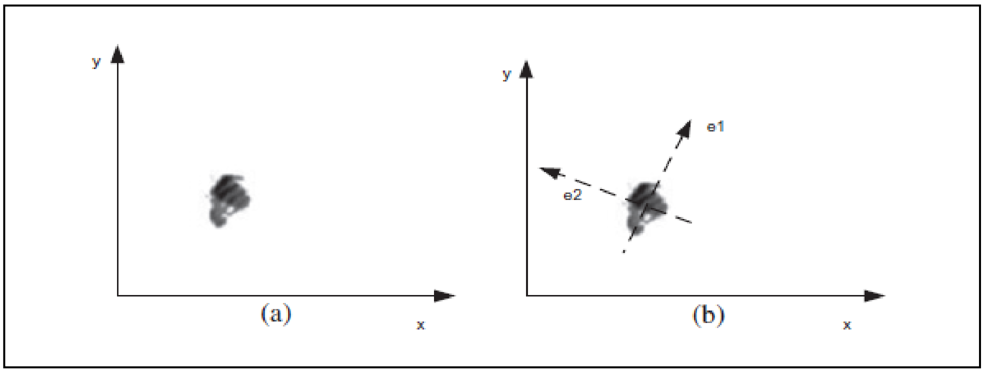


Figure 3.5: Transformation from hand to Eigen space (a) Coordinates and (b) Eigen vectors [Zaki & Shaheen 2011].

Zaki [Zaki & Shaheen 2011] uses PCA where the hand representation is transformed from the image coordinates to Eigen vector space. After vector rotation the largest Eigen vector is aligned with the mid of data as shown in Figure 3.5. He used three HMMs for every sign, one for each feature: PCA Sequence, Kurt Pos Sequence and MCC Sequence. Shin [Shin & Lee+ 2006] presents gesture extraction and recognition using entropy analysis and low level image processing functions. Lee [Lee & Lee+ 2004] also uses entropy to obtain color information. He uses pictorial information system (PIM) to quantify the entropy of the image using the (3.5).

$$\mathrm{PIM} = \sum_{i=0}^{L-1} h(i) - \mathrm{Max}_j h(i) \qquad (3.5)$$

where $h(i)$ is the i^{th} histogram value of each image or block. To acquire the PIM value, all pixels in each block are subtracted from the maximum frequency in the histogram model.

Lu [Lu & Shark+ 2009] implements a system for 3D gesture recognition where he fuses different positions of a gesture using coordinate transformations and then uses stored pre-specified gestures for gesture recognition. Stefan [Stefan & Athitsos+ 2008] uses Dynamic Space-Time Warping (DSTW) [Alon & Athitsos+ 2005] to recognize a set of gestures. This technique doesn't require hands to be correctly identified in each frame.

Zou [Zou & Xiao+ 2009] uses Deterministic Finite State Machine (DFSM) to detect hand motion and then applies rule based techniques for gesture recognition. He defines the gesture into two category based on motion. These categories include linear and arc shaped gestures. Tarrataca [Tarrataca & Santos+ 2009] uses convex hull method based clustering algorithm for posture recognition. Chang [Chang & Liu+ 2008] uses a feature alignment approach based on curvature scale space to recognize hand posture.

3.4 Implementation Tools

Mostly researchers who study image processing, use MATLAB® with the image processing toolbox. A few also use C++. Lu [Lu & Shark+ 2009], Lee [Lee & Chun 2009] and Zou [Zou & Xiao+ 2009] use C++ for implementation on Windows XP®.

Lu [Lu & Shark+ 2009] and Lee [Lee & Chun 2009] use Microsoft® Foundation Classes (MFC) to build user interface and control. Intel OpenCV Library is also popular in vision application processing. Even OpenCV has been used with MATLAB® to implement few systems [Suk & Sin+ 2010]. Stergiopoulou [Stergiopoulou & Papamarkos 2009] uses Delphi to implement the HGR system using SGONG network.

3.5 Accuracy

Different systems have been discussed in this chapter as well as the approach used to implement them. The systems' accuracy w.r.t. hand gesture recognitions is discussed. GREFIT [Nolker & Ritter 2002] system is able to detect finger tips even when it is located in front of the palm. It is able to construct a 3D image of the hand that is visually comparable. Nguyen [Nguyen & Pham+ 2009] claims that the results are 90-95% accurate for open fingers, but only 10-20% for closed fingers. Figure 3.6 presents a scenario in which closed or bent fingers are located in front of the palm. Hence, the skin color detection cannot differentiate between the palm and the finger. According to Nguyen, the image quality and morphology operator are the main reasons for low accuracy in detection.

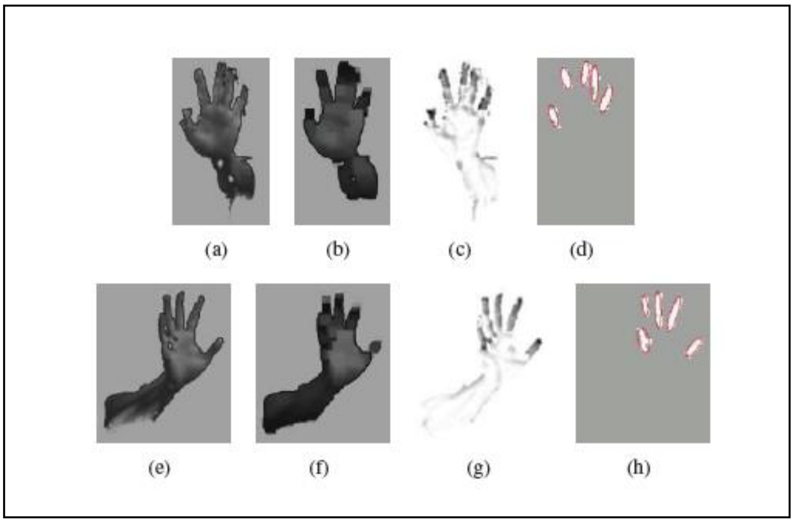


Figure 3.6: Result of finger extraction using grayscale morphology operators and object analysis [Nguyen & Pham+ 2009] which work for bent finger also, but with a lower accuracy i.e. 10-20%.

Raheja [Raheja & Shyam+ 2010] claims approximately 90% accuracy in his results if the lighting conditions are good. Hu [Hu & Yu+ 2000] uses six different parameters to control the performance of the system. For scenarios involving a significant amount of noise, the noise is controlled by employing two parameters. Stergiopoulou [Stergiopoulou & Papamarkos 2009] claims about 90.45% accuracy, though the hidden finger is not detected in his approach. Morimoto [Morimoto & Miyajima+ 2007] claims for his system approximately 91% accuracy after applying normalization. Ng [Ng & Ranganath 2002] claims 91.9% correct results for his approach that involves a combination of HMM and RNNs. Huang [Huang & Hu+ 2010] claims 93.7% recognition results using Gabor filters.

Lee [Lee & Lee+ 2004] shows results for six kinds of gestures with a recognition rate of more than 95%. The focus of the research is only on whether the finger is bent and not on the degree of bending. Stefan [Stefan & Athitsos+ 2008] achieves 96% accuracy over 300 tests. He also states that parallel image processing and pattern matching operations are not real time compatible in MATLAB®, but can be faster if implemented in C++. For running gestures like Bye and showing a direction, Suk [Suk & Sin+ 2010] claims 80.77 % accurate results.

3.6 Conclusion

It is discussed in this chapter that a wide range of literature is available on open hand gesture recognition. However, little research work has been performed in the area of static closed fingers identification. Moreover, no previous study has considered the bent fingers' angle calculation in 2D. Nolker has conducted such a modeling only in 3D space.

In order to recognize the hand gesture, one needs to extract the required information from the video and for that the capturing image sequence need to be segmented in real time. The pre-processing of input images is required for segmentation, noise removal and smoothen them. In the next chapter, the pre-processing is discussed for hand segmentation and noise removal to obtain the region of interest when input is a live stream of hand gesture images, and a novel faster algorithm is also presented to reduce processing time.

Chapter 4

Hand Image Segmentation

It was previously discussed in Chapter 3 that a number of upcoming as well as existing applications are based on hand gesture recognition (HGR) techniques involving a bare hand. Such techniques allow a natural communication with machines. HGR based systems face many problems in skin segmentation due to luminance and intensity in images which is a major cause of noise in the pre-processed results. The HGR based systems mostly make assumptions about the hand direction. This causes restrictions in the natural expression of humans. Many systems are based on the assumption that the users have to show the hand in straight position, with the fingers pointing upward. Processing time is another key factor that needs to be considered when designing image based processing algorithms.

In this chapter the focus is on direction invariant segmentation of a natural hand with real time performance. It is considered that there is no restriction on the gesture direction. Moreover, in the context of natural computing, there is no requirement for gloves, sensors or colour strips to segment the hand. The only assumption is that the user presents the hand to the system such that the palm faces the system while the direction of the hand is not restricted. The user is free to move the hand in any direction naturally as the hands move. This chapter presents a novel image cropping pre-processing algorithm, which fastens the gesture recognition process. This is done by performing cropping and hence reducing the number of processing pixels. A detailed discussion on hand geometry parameters (HGP) i.e. fingertips and COP detections is presented in Chapter 6. Figure 4.1 presents a block diagram of the entire process.

A novel method of hand segmentation with the help of MS KINECT is also discussed in this chapter. KINECT facilitates by providing the depth information of foreground objects. The gesture parts are segmented using the depth vector given by KINECT depth sensor.

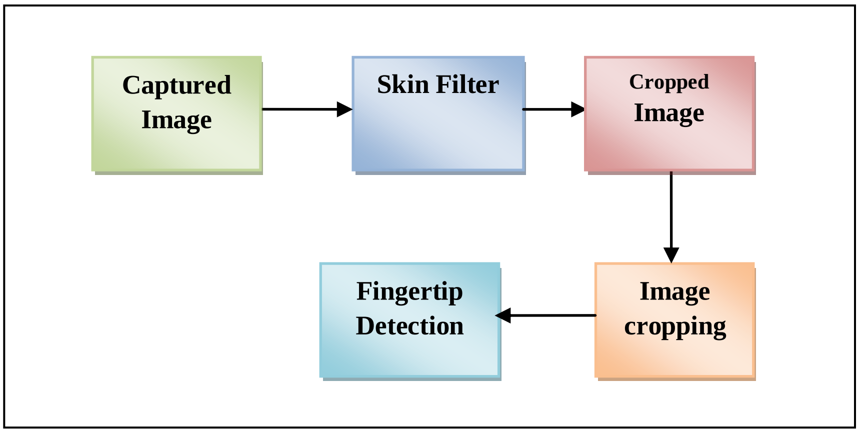


Figure 4.1: Algorithm Flow for the pre-processing Method.

4.1 Related Approaches

A lot of work has been done in this area of dynamic hand gesture recognition using different techniques. In Chapter 3, it was discussed that there are several issues in the existing approaches that are yet to be solved. Garg [Garg & Aggarwal+ 2009] used 3D images in his method to recognize the hand gesture. However, this process is complex and also not time-efficient. The processing time is one of the very critical factors in real time applications [Ozer & Lu+ 2005]. Aznaveh [Aznaveh & Mirzaei+ 2008] presented a RGB vector-based method for skin detection in images.

Researchers [Brown & Thomas 2000][Crowley & Berardand+ 1995][Quek & Mysliwiec+ 1995][Tomita & Ishii 1994] have assumed that the hand is always pointing upward to get precise localization. Few other studies are dependent on specialized instruments and setup like the use of infrared camera [Oka & Sato+ 2002a], stereo camera [Ying & Song+ 2008], a fixed background [Crowley & Berardand+ 1995][Quek & Mysliwiec+ 1995] or use of markers on hand for segmentation. Researchers [Oka & Sato+ 2002a][Oka & Sato+ 2002b][Sato & Kobayashi+ 2000] have used infrared cameras to get a reliable segmentation. Generally image based models operate pixel by pixel and perform hand segmentation working only on skin pixels, which is the region of interest. However, most hand segmentation methods cannot perform accurate hand segmentation under some conditions for instance, fast hand motion, cluttered background, poor light condition [Hardenberg & Berard 2001]. If the hand segmentation is not accurate, then the detection of fingertips could become questionable.

Few researchers [Crowley & Berardand+ 1995][Hardenberg & Berard 2001][Keaton & Dominguez+ 2002][Quek & Mysliwiec+ 1995][Tomita & Ishii 1994][Wu & Shan+ 2000] in their work limit the degree of the background clutter, finger motion speed or light conditions to get a reliable segmentation. Few others also use 3D mapping using specialized devices like MS KINECT for hand segmentation. This chapter describes a novel method of dynamic hand segmentation without using any kind of sensor or marker.

Figure 4.2: System prototype.

4.2 Hand Segmentation

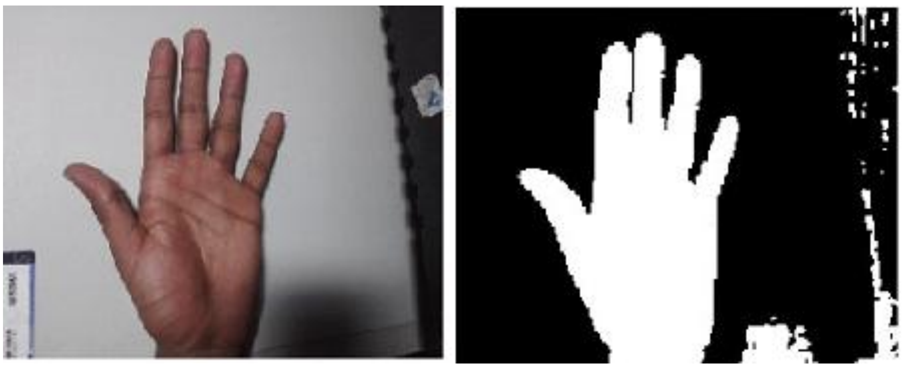
Video is a sequence of image frames taken at a fixed rate. In this experimental setup all images are captured continuously with a simple web camera in 2D and are processed one by one as shown in Figure 4.2. The process of hand segmentation is discussed in three steps. Firstly, an HSV colour space based skin filter is applied on the images for hand segmentation. Secondly, an intensity based histogram is generated for the hand direction detection. Thirdly, the image is cropped so that the resultant image is composed of only the gesture pixels.

4.2.1 Skin Filter

The skin filter used on the input image can be based on HSV or YC_bC_r color space to reduce the light effect to some extent. In the HSV color space the skin is filtered using the chromacity (hue and saturation) values while in the YC_bC_r color space the C_b, C_r values are used for skin filtering. A HSV color space based skin filter is applied to the current image frame for hand segmentation. This color space separates three components: hue (H), saturation (S) and brightness (I, V or L).

Essentially HSV color spaces are deformations of the RGB color cube and they can be mapped from the RGB space via a nonlinear transformation. The reason behind the selection of this color space in skin detection is that it allows users to intuitively specify the boundary of the skin color class in terms of the hue and saturation. As I, V or L give the brightness information, they are often dropped to reduce illumination dependency of skin color. The result of applying skin filter is shown in Figure 4.3.

The skin filters are used to create a binary image with the background in black color and the hand region in white. Binary images are bi-level images where each pixel is stored as a single bit (0 or 1). Smoothening of the resultant image is needed, as the output image may contain some jagged edges. This binary image is smoothened using the averaging filter.



(a) (b)

Figure 4.3: Skin filtering results (a) Initial hand image (b) Binary silhouette.

There can be false positives in the results due to falsely detected skin pixels or some skin color objects (like wood) in the background. This can generate few unwanted spots in the output image as shown in Figure 4.3(b). Hence, to remove these errors the biggest Binary Linked Object (BLOB) is considered as the hand mask and rest are considered in the background as shown in Figure 4.4(a). The biggest BLOB represents hand coordinates as ‘1’ and ‘0’ for the background. The filtered hand image obtained after removing all errors is shown in Figure 4.4(b). The only limitation of this filter is that the BLOB for the hand should be the biggest one. In this masking, the background is eliminated. Therefore, falsely detected skin pixels do not exist in the background.

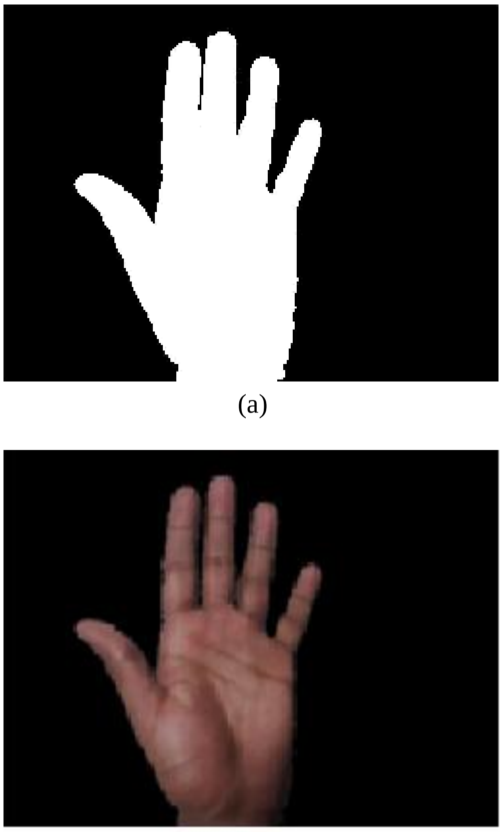


Figure 4.4: BLOB Results (a) Biggest BLOB (b) Hand after filtration.

4.2.2 Hand Direction Detection

In this system, the user can give direction free input by presenting a hand gesture to the camera. For obtaining better and unambiguous results, it is necessary to find out the direction of the hand. For doing so a 4-way scan of the pre-processed image is performed as shown in Figure 4.5 and histograms are generated based on the skin color intensity in each direction. In all four scans the maximum value of skin pixels is selected from the histograms. It is oblivious that the maximum value of skin pixels in the image represents the wrist end and the opposite end of the scan represents the finger end. The functions employed for generating the intensity histograms are presented in (4.1) and (4.2).

$$H_x = \sum_{y=1}^{n} imb(x,y) \tag{4.1}$$

$$H_y = \sum_{x=1}^{m} imb(x,y) \tag{4.2}$$

where *imb* represents the binary silhouette and *m* and *n* represent the rows and columns respectively of the matrix *imb*.

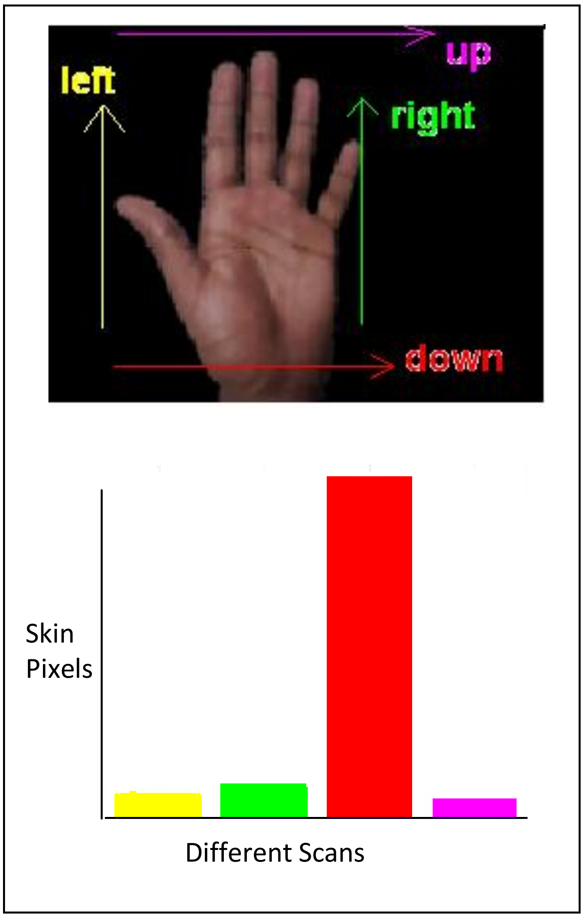


Figure 4.5: Image scanning and corresponding bars.

The yellow bar shown in Figure 4.5 corresponds to the first skin pixel in the binary silhouette scanned from the left direction. The green bar corresponds to the scan performed from the right direction, the red bar corresponds to the scan performed from the downward direction and pink bar corresponds to the scan performed from the upward direction.

It is clear that the red bar has a higher magnitude compared to the other bars for this particular gesture image. Hence, it can be inferred that the wrist end is in the downward direction of the frame and consequently the direction of fingers is in the upward direction. Hence, the direction from the wrist to the fingers is identified.

4.2.3 Hand Cropping

In Section 4.2.1 the region of interest has been detected from the image frame, while the remaining part of the image is rendered useless. The part of the image shown in Figure 4.4(b) that is black (which is the undesired part of the image) forms a significant portion of the complete image. Hence, if it is possible to reduce or crop the image such that only the ROI is present, a significant amount of computational time can be reduced. In the histograms which was generated in Section 4.2.2, it was observed that at the point where wrist ends, a steeping inclination of the magnitude of skin pixels in the histogram starts, the slope *m* of which can be obtained from

$$m = \frac{y2-y1}{x2-x1} \tag{4.3}$$

Figure 4.6 presents the intensity histogram for skin colour where a sharp inclination is clearly visible. Now, consider the last pixel of the skin colour in each direction and consequently obtain the tangent on that point. The image is cut at these tangents in all four directions. As the hand direction is already known from Section 4.2.2, start a scan from the wrist end on the resultant image of Section 4.2.1. The inclination point in the binary image is obtained and the image is cut at this point. In other three directions, start a scan in the image and stop when the first skin colour pixel in each direction is obtained.

The points corresponding to the first skin pixel known from performing scanning from all sides are obtained. Then, crop the image at these points by drawing virtual tangents at these points. The expressions, based on which the image cropping is performed, are given by:-

$$imcrop = \begin{cases} origin_{image} & ; Xmin < X < Xmax \\ & ; Ymin < Y < Ymax \\ 0, & ; elsewhere \end{cases} \tag{4.4}$$

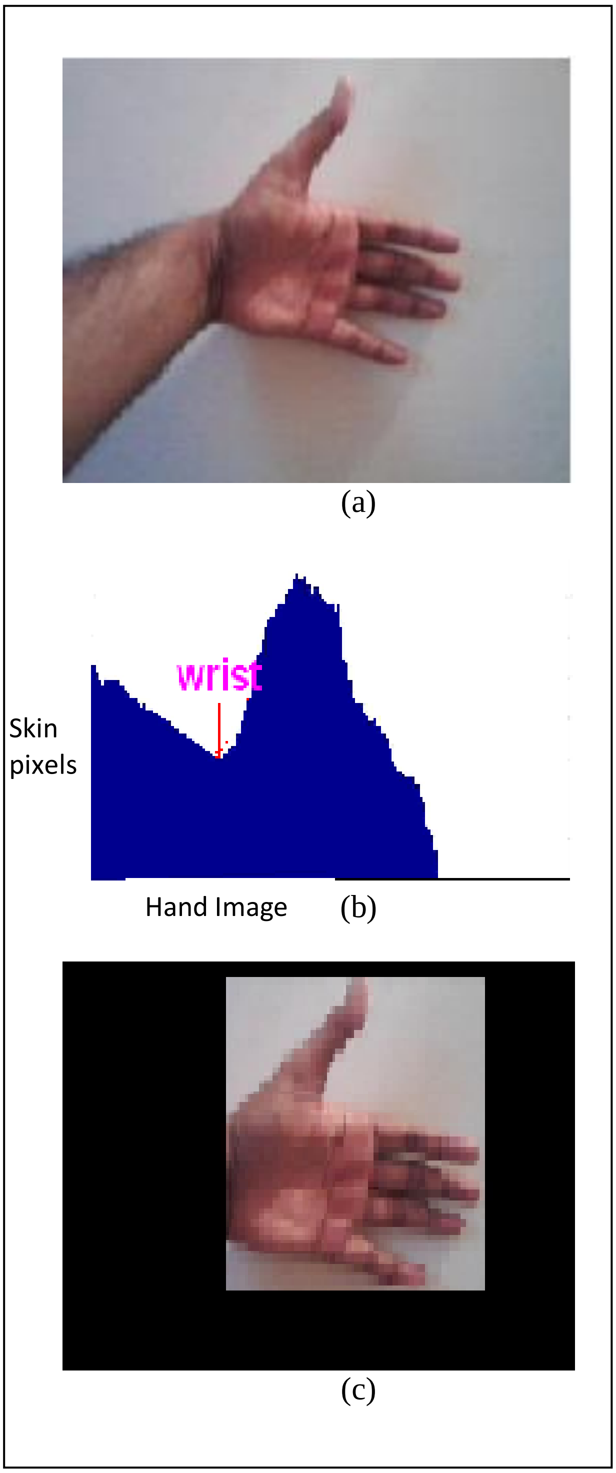


Figure 4.6: Hand Cropping Process: Images shown are (a) Initial image, (b) Histogram of binary silhouette where the wrist end is clearly detected (c) Cropped hand image.

where *imcrop* represents the cropped image and *Xmin*, *Ymin*, *Xmax* and *Ymax* represent the boundary of the hand in the image

Some results with processing steps for hand cropping are shown in Figure 4.7. In all of the histograms presented in Figure 4.7, it is clear that at the wrist point a steeping inclination begins in the scanning direction.

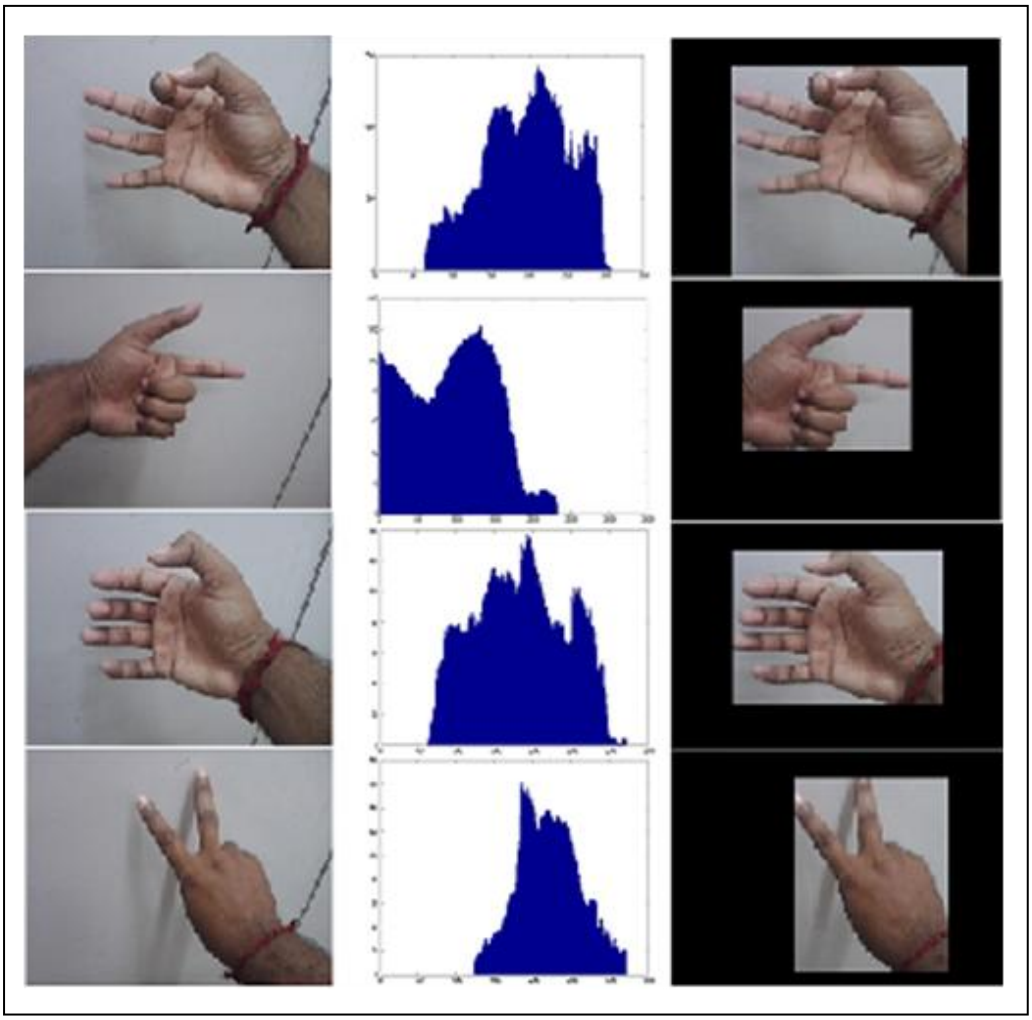


Figure 4.7: Results of the hand cropping process obtained from live images.

4.3 Hand Segmentation Using KINECT

Many researchers have proposed different methods for dynamic hand gesture recognition using various sensors. This has led to an era of research that is focussed on the existing problem in the area of HGR of obtaining the depth information of the object. Microsoft KINECT is an example. KINECT is able to detect individual finger motion in three dimensions. A model of KINECT is shown in Figure 4.8.

Figure 4.8: MS KINECT.

4.3.1 Microsoft KINECT Architecture

KINECT provides a RGB view and an infrared view of the object as well as the distance information of the object. The internal architecture of MS KINECT is shown in Figure 4.9. It consists of an infrared camera and a PrimeSense sensor to compute the depth of the object while the RGB camera is used to capture the images. As Frati [Frati & Prattichizzo 2011] stated “It has a webcam–like structure and allows users to control and interact with a virtual world through a natural user interface, using gestures, spoken commands or presented objects and images

It is clear that KINECT is a robust device and can be used in various complex applications. The depth images and RGB images of the object can be obtained at the same time. It has a 3D scanner system called Light Coding which employs a variant of image-based 3D reconstruction. The depth output of KINECT is 11 bit with 2048 levels of sensitivity [WIKIb].

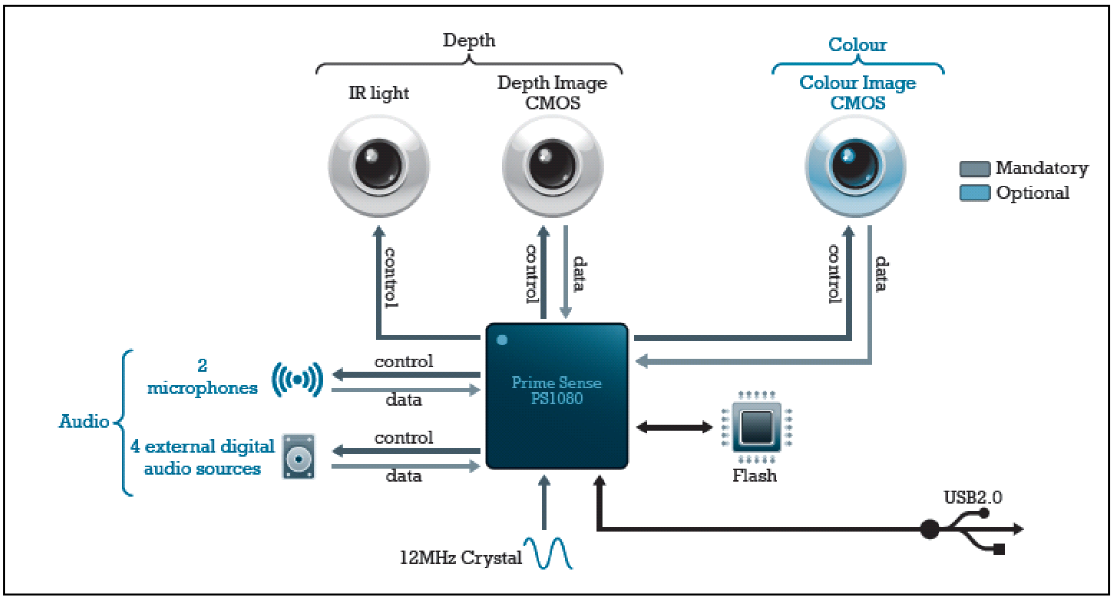


Figure 4.9: MS KINECT Architecture [TET 2011].

4.3.2 Related Approaches

Garg [Garg & Aggarwal+ 2009], Nolker [Nolker & Ritter 2002] and a few researchers have used 3D models in their techniques for recognizing the hand gesture. However, this process is complicated and inefficient. It is essential that due importance is given to accuracy as well as efficiency because processing time is a very critical factor in real time applications. Few other methods based on specialized instruments for better hand segmentation [Oka & Sato+ 2002a][Ying & Song+ 2008][Crowley & Berardand+ 1995][Quek & Mysliwiec+ 1995] or use of markers on hand have been proposed. These methods are more robust and reliable as they are based on the depth information provided by the KINECT, while for a simple webcam these are based on segmentation methods.

4.3.3 Hand Segmentation in 3D

It is discussed previously that the infrared sensor provides the depth information of objects that are in its view. The different depth values are represented by different colours on the screen. The image with its depth information is presented in Figure 4.10.

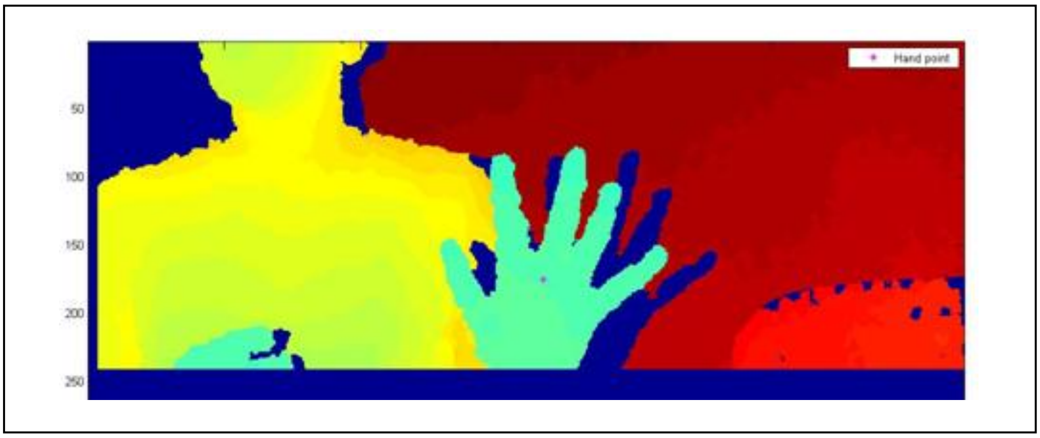


Figure 4.10: Depth image acquired using KINECT.

The depth value d_{raw} of a point in 3D can be defined through calibration procedure [Frati & Prattichizzo 2011], namely

$$d = K \operatorname{tang}(Hd_{raw} + L) - O \quad (4.5)$$

where d is the depth of that point in cm, H equals 3.5x10-4rad, K equals 12.36cm , L equals 1.18rad and O equals 3.7cm. This tangential approximation has a sum of squared difference of 0.33cm^2 for the calibration data. After getting the depth information, the 3D coordinates of any object can be computed. Let (i, j) be the coordinates of the perspective projection of any point onto the KINECT camera frame that forms a 3D system for this point represented by (x, y, z). Then, the 3D vectors can be obtained from [Fisher 2010]

$$x = (i - c_x)f_x d \quad (4.6)$$

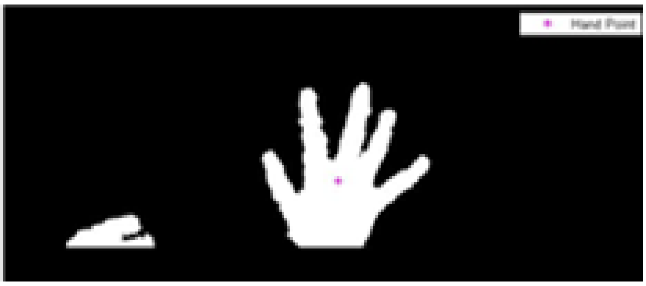
$$y = (j - c_y)f_y d \quad (4.7)$$

$$z = d \quad (4.8)$$

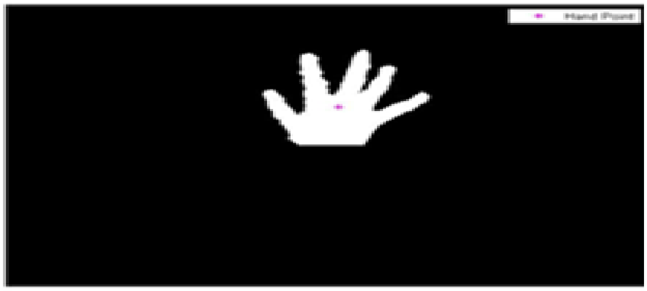
where f_x equals 0.5942143, f_y equals 0.5910405, c_x equals 339.3078 and c_y equals 242.739.

After obtaining the 3D points, hand tracking and point detection is performed using NITE modules, which use Bayesian Object Localization for hand detection. OpenNI modules, which provide C++ based APIs, is used for hand detection and tracking.

The depth image is segmented after applying a calculated threshold on the depth of hand points and the hands are detected by choosing the blob which contains the hand point. The result obtained when this process is implemented is presented in Figure 4.11.



(a)



(b)

Figure 4.11: Segmentation using KINECT Results (a) Threshold image, (b) Image of one hand.

4.4 Conclusion

In this chapter techniques are presented for hand segmentation implemented on a live stream of images. The hand images from live video are segmented using a simple webcam as well as the MS KINECT. Encouraging results have been obtained. The presented method is able to segment image irrespective of the hand direction. This is a stepping stone towards the target i.e. hand gesture recognition.

Different users of the system would have different skin colours and the skin colour also would be varied in changed light intensity. For the robust hand gesture recognition, a light intensity invariant method is needed. This light conditions invariant HGR technique is discussed in Chapter 5.

Chapter 5

Light Invariant Hand Gesture Recognition

Recently there has been a growing interest in the field of light invariant recognition. For advanced applications a system can be setup in the laboratory with ideal conditions. However, in practical scenarios the hand gesture recognition systems may have applications in various environments. The light intensity may not be same everywhere, hence a robust system that operates in all types of light conditions is required.

In image processing applications, the light intensity plays an important role because it significantly affects the segmentation of the ROI from original image frame. If the light intensity changes, then the threshold for skin filter also has to be changed. This motivates the development of techniques that are applicable to different light intensities. As this thesis is devoted to the natural interaction with machines using hand gestures, in this chapter the analysis of the effect of light intensity on bare hand gesture recognition is performed. The light intensity at different times of the day, specifically, every two hours, is considered.

The hand gestures are interpreted by the system during the hand gesture recognition process, whether it is a predefined valid gesture or not. If the gesture is included in the list of the gestures then the system responds to the corresponding action as predefined in the system. The light intensity in predefined gesture and light intensity in the current system can be different, but the system is supposed to recognize it as same gesture.

5.1 Related Approaches

There are many previous studies that have extracted certain features of the hand for gesture recognition in order to make them robust. Keskin [Keskin & Aran+ 2005] have developed an automatic tutor for sign language. Some common features extracted include hand silhouettes [Shimada 1998] [Messery 1998][Sonka & Hlavac+ 1999], contours [Starner & Pentland 1995], key points distributed along the hand i.e. fingertips and joints. Yoon [Yoon & Soh+ 2001] have also proposed a recognition scheme using combined features of location, angle and velocity. Locken [Locken & Fitzgibbon 2002] proposed a real time gesture recognition system, which can recognize 46 MAL, letter spelling alphabet and digits. There is however still a requirement for a system for efficient and robust technique finger detection. Identification of a hand gesture can be performed in many ways, which are selected on the basis of the problem to be solved, as is discussed in Chapter 3.

5.2 Pattern Recognition

The goal of pattern recognition is to classify the objects of interest into one of a number of categories or classes [Therrien 1989]. The objects of interest are generally called patterns. They can be printed letters or characters, biological cells, electronics waveforms or signals, states of a system or any other items that one may desire to classify. Any pattern recognition system consists of two components, namely feature transformation and classifier [Therrien 1989] (see Figure 5.1).

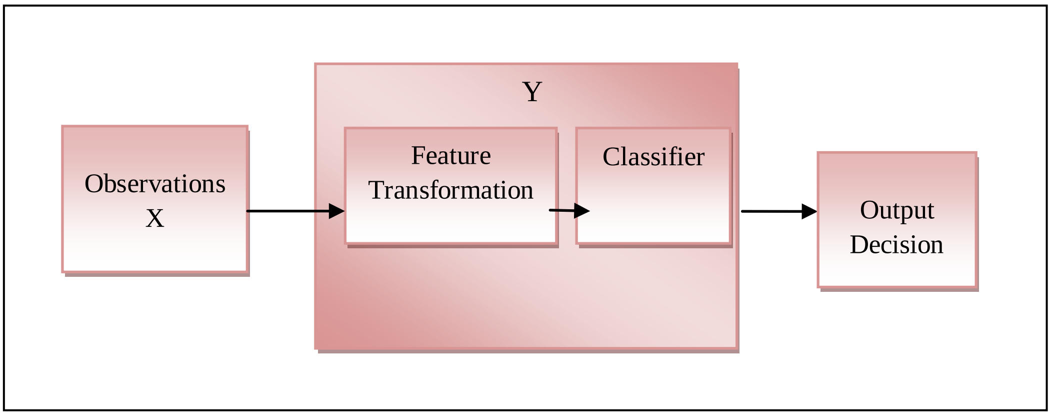


Figure 5.1: Approach of feature extraction.

The observation vector X is first transformed into another vector Y whose components are called features. These are intended to be fewer in numbers than the observations collected, but must collectively represent most of the information needed for the classification of patterns [Therrien 1989]. By reducing the observations to a smaller number of features, one may design a decision rule which is more reliable. There are several transformations that can be applied in order to obtain better features. However, the feature extraction is mostly problem domain dependent.

The feature vector Y is passed to the classifier, which makes decisions about the pattern. The classifier essentially partitions the feature vector space into a number of disjoint regions as shown in Figure 5.2. If the feature vector corresponding to the pattern falls into region R_i, the pattern is assigned to class ω_i.

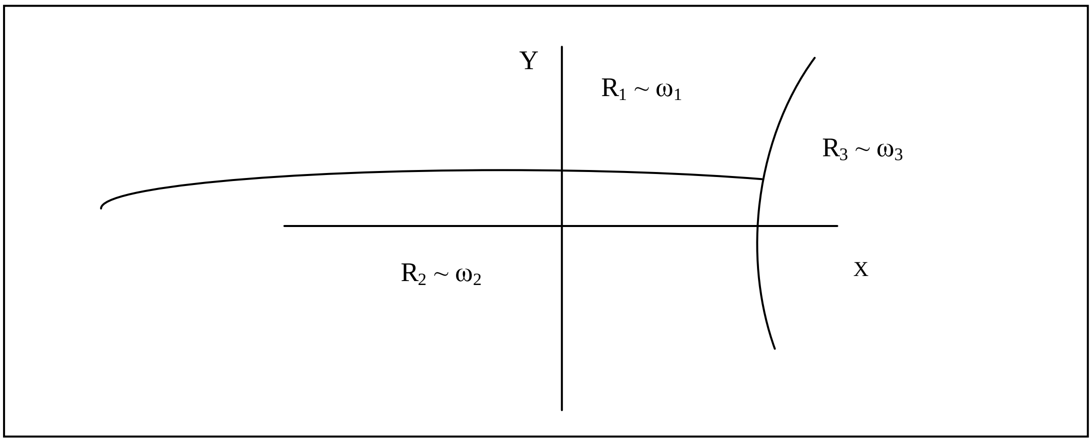


Figure 5.2: Partitioning of feature space.

For a pattern recognition problem, feature extraction is a major step. The goal of feature extraction is to find a transformation from an n-dimensional observation space X to a smaller m-dimensional feature space Y that retains most of the information needed for pattern classification. There are two main reasons for performing feature extraction. First, the computational complexity for pattern classification is reduced by dealing with the data in a lower dimensional space. Secondly, for a given number of training samples, one can generally obtain more accurate estimates of the class conditional density functions and thus formulate a more reliable decision rule [Therrien 1989]. In the past several methods have been used for feature extraction. Generally, the features are suggested by the nature of the problem.

5.3 Orientation Histogram

Orientation Histogram (OH) technique for feature extraction was developed by McConnell [McConnell 1986]. The major advantage of this technique is that it is simple and robust to lighting changes [Freeman & Roth 1994]. If the pixel-intensities approach is taken, certain problems arise due to varying illumination [Messery 1998]. If pixel by pixel difference for the same gesture is taken from two different images, while the illumination conditions are different, the distance between them would be large. In such scenarios the picture itself acts as a feature vector.

The main motivation for using the orientation histogram is the requirement for lightening and position invariance. Another important aspect of gesture recognition is that irrespective of the orientation of the hand in different images, for the same gesture system must produce the same output. This can be done by forming a local histogram for local orientations [Liang & Ouhyoung 1998]. Hence, this approach must be robust for illumination changes and it must also offer translational invariance.

Another important requirement is that it should match with the same gestures regardless of where they occur in the image. The pixel levels of the hand would vary considerably with respect to light, on the other hand the orientation values remain fairly constant. The local orientation can be calculated from the direction of the image gradient. Then, the local orientation angle θ will be a function of position x and y, and the image intensities $I(x, y)$. The angle θ is defined as:

$$\theta(x, y) = \arctan\,[I(x, y) - I(x-1, y),\ I(x, y) - I(x, y-1)] \tag{5.1}$$

Now form a vector Φ of N elements, with the i^{th} element showing the number of orientation elements $\theta(x, y)$ between the angles $\frac{360^0}{N}\left[i - \frac{1}{2}\right]$ and $\frac{360^0}{N}\left[i + \frac{1}{2}\right]$. Where Φ is defined as:

$$\Phi(i) = \sum_{x,y} \begin{cases} 1 & \text{if } \left|\theta(x,y) - \frac{360^0}{N} i\right| < \frac{360^0}{N} \\ 0 & \text{otherwise} \end{cases} \tag{5.2}$$

5.4 Light Invariant System

The recognition system works on the principle of the computer vision in 2D space. The basic methodology has been shown in Figure 5.3. The system has an interface with a small camera which captures users' gestures. Input to the system is image frame of moving hand in front of a camera captured as a live video. The preprocessing of image frame was done as discussed in chapter 4. The result image would be ROI i.e. only gesture image. Once the ROI is available, next step is to find out feature vectors from the input image to recognize it with the help of ANN.

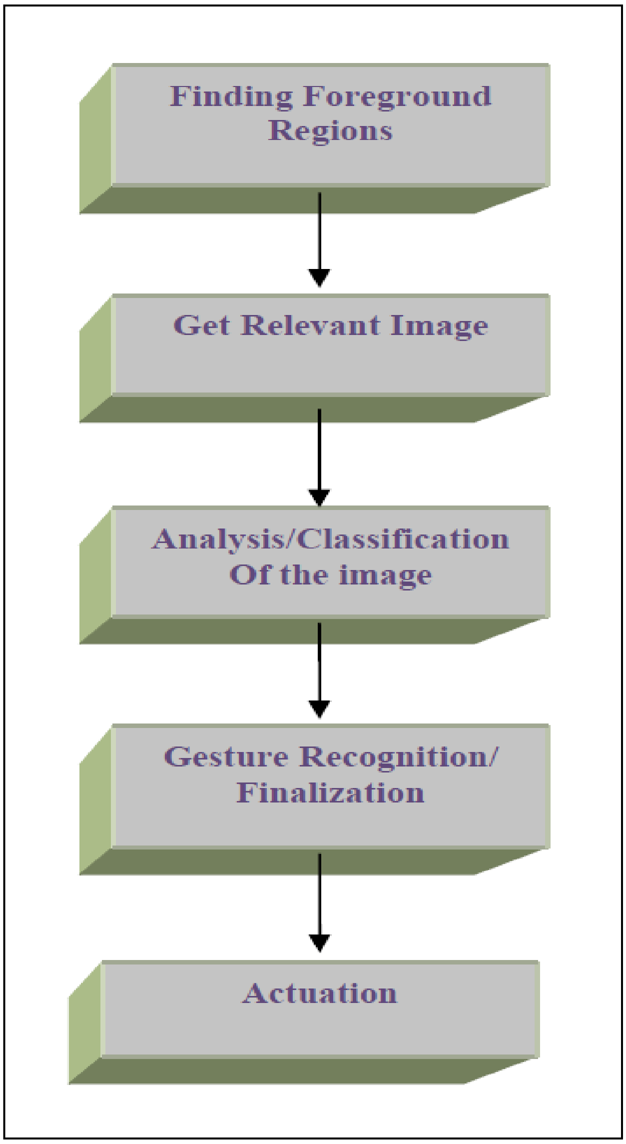


Figure 5.3: Gesture recognition methodology.

As this system was for research purpose, only 6 different gestures are taken in the data set as many researchers were also have tested their methods with 6 gestures in the past. These six different gestures used in this research, are shown in Figure 5.4. The images of each gesture, used for ANN training, were different in the skin color and light intensity.

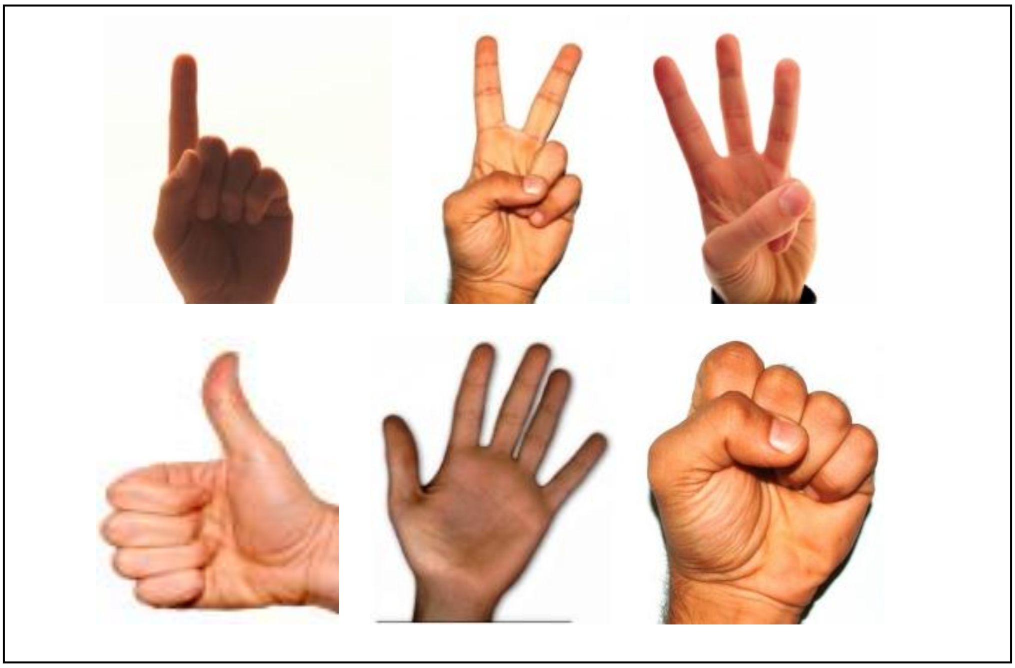


Figure 5.4: Hand Gestures to be used in the System.

Once the gesture would get recognized the corresponding action takes place which could be associated with it. In developed system the audio description of the matched gesture was attached as corresponding action. On recognition of the gesture, the audio file corresponding to the recognized gesture would be played.

The implementation of system is discussed in different steps:

5.4.1 Data Collection for Training Purpose

The training images for the ANN were collected from different sources including online search and manually collection. This was to ensure the robustness of the method as images from different sources would contain different skin color, different light intensity and different hand shape. Skin color has property that it looks different in different light intensities. Fourteen different images are used for each gesture to train ANN.

5.4.2 Pre-Processing of Images

The ROI is needed from the images with random background for training purpose and for recognition also. If the images have only ROI then the training of the ANN would be better. All images, used for training, were converted into same resolution as the webcam was capturing the video. The preprocessing of the images is described in chapter 4.

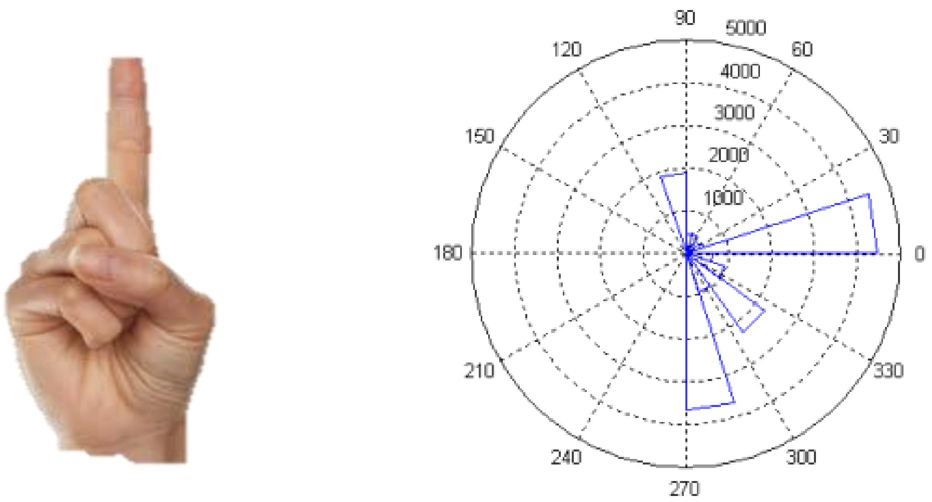
5.4.3 Feature Extraction

To train the ANN and for gesture recognition, the features need to be extracted from the pre-processed images. The algorithm used for feature extraction results in an orientation histogram for a given gesture. The same algorithm was applied for all the gestures present in the database in order to generate a training pattern. These training patterns were stored and applied to the neural network to train it. For gesture recognition purpose the same algorithm was applied. The algorithm is described in steps below:

1. This algorithm is based on orientations of edges, so we have to find the edges in pre-processed images. Two simple filter vectors were used to for this, for X direction X= [0 -1 1] and for Y direction Y= $[0\ -1\ 1]^T$.
2. They were applied to each pixel in the ROI image to calculate image gradients dx and dy. The local orientation was calculated using image gradients and then arctan transformation was applied as shown in (5.1). This would result in gradient orientation vector.
3. The image blocks were rearranged into columns using MATLAB®. This was converted from radian values to degrees. So, a scan could be done on the orientation elements values ranging from 0^0 to 190^0. As mentioned in the (5.2), vector Φ of N elements where N=19 is obtained.
4. The column matrix was used in order to plot orientation histogram. Using these plots the closeness of gesture recognition could be identified.

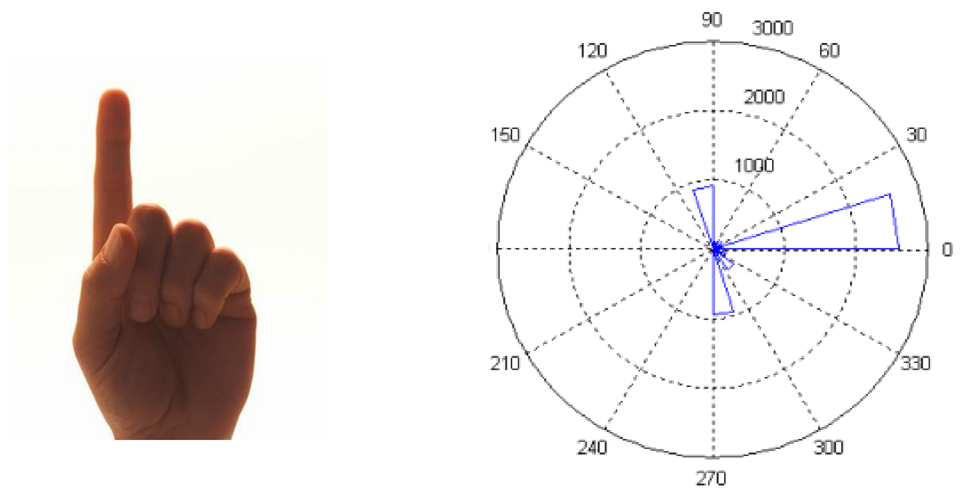
Now average the adjacent histogram bins in order to reduce the noise and allow interactions. For this research N=19 was used in step 3 of algorithm and this is purely an empirical estimate after observing the results with various N values like 20, 25, 15 etc. Euclidean distance can also be used to measure the difference between the histograms of two gestures. This is given in (5.3).

$$\sum_i (\Phi_1(i) - \Phi_2(i))^2 \tag{5.3}$$



(a) (b)

Figure 5.5: (a) Gesture I and (b) OH of Gesture I.



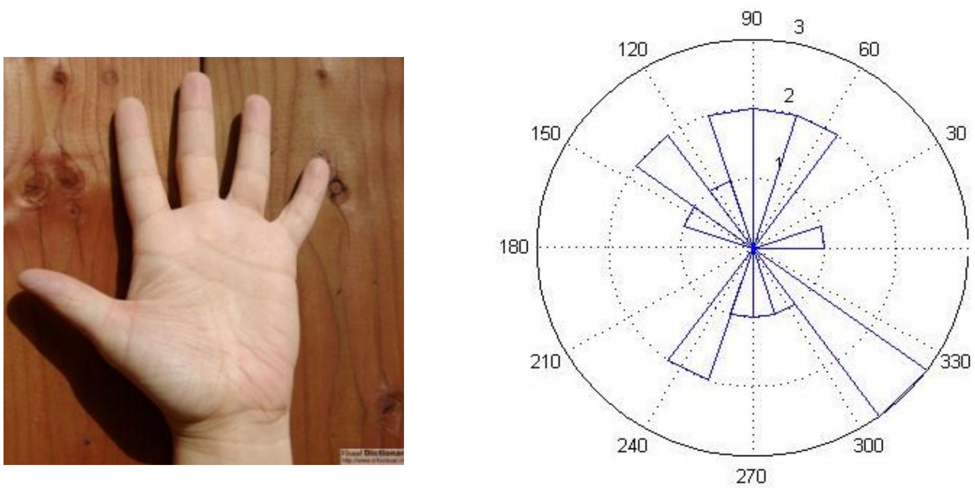
(a) (b)

Figure 5.6: (a) Gesture II and (b) OH of Gesture II.

5.4.4 Light Invariant Gesture Recognition

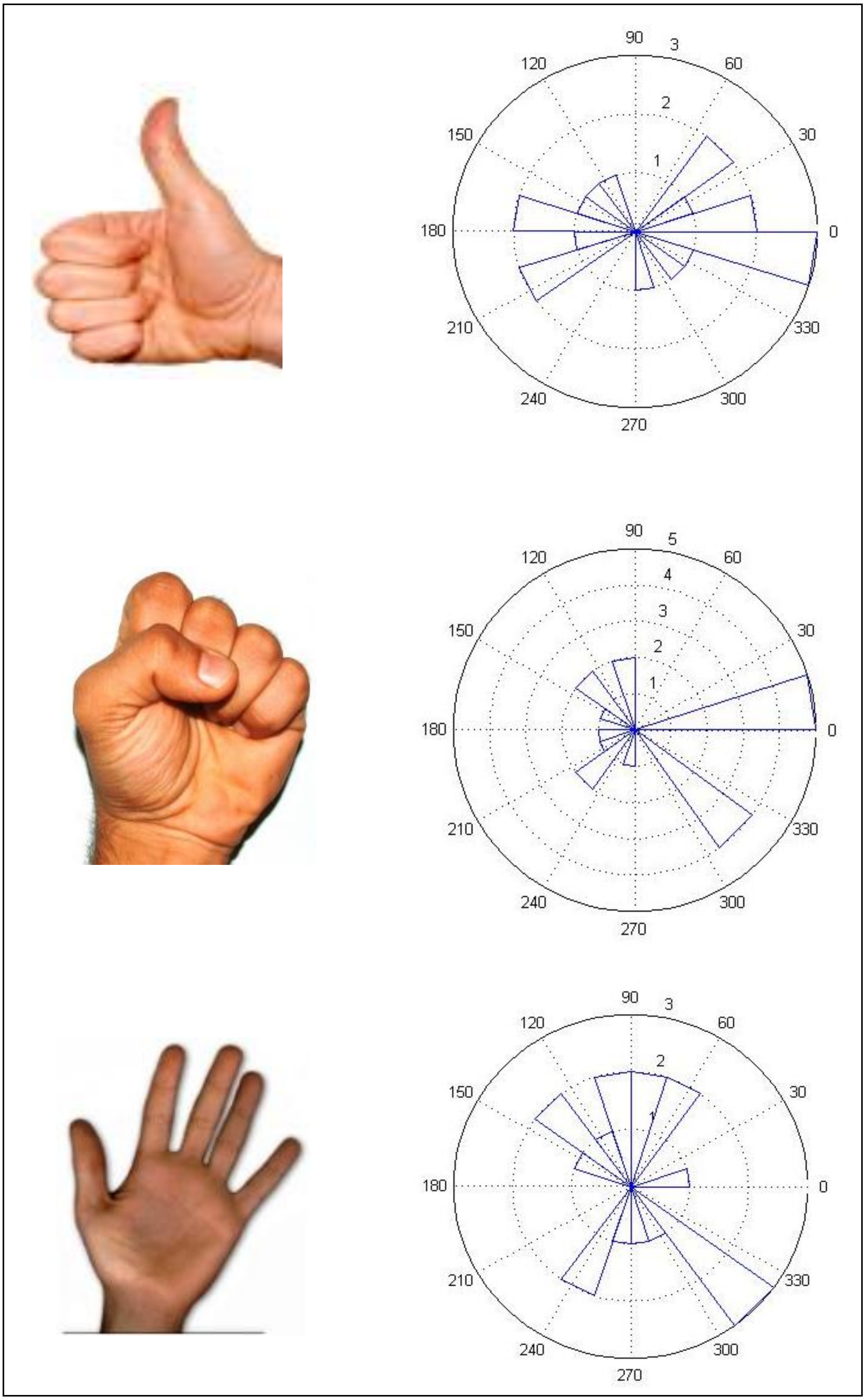
Gestures should be recognized same regardless of where they occur within the camera's field of view. This translation invariance can be achieved by the drastic step of ignoring position altogether, simply tabulating a histogram of how often each orientation direction occurred in the image. Clearly, this throws out some information, and few distinct images will be confused by their orientation histograms. For the purpose of feature extraction illustration, take one example of forefinger gesture raised and their corresponding OH as shown in Figure 5.5 and 5.6.

Here it can be seen that the similarity between these orientation histograms even the skin color were very much different. This skin color difference could be because of different people or the same person in different light intensity. These similarities would be more clearly observed if we plot the OH for another gesture. It is a general assumption that positions of fingertips in the human hands are relative to the palm and it is almost always sufficient to differentiate a finite number of different gesture [Ahmad & Tresp 1993] [Davis & Shah 1994][Kuno & Sakamoto+ 1994]. Let's consider the gesture as all five fingers open and it's OH as shown in Figure 5.7. From this it is clear that OH plotted for two different gestures would be very much different while for same gesture it would show same OHs only amplitude of vector can vary w.r.t. to light intensity.



(a) (b)

Figure 5.7: (a) Gesture III and (b) OH of Gesture III.


90
3
120
60
2
150
30
1
180
0
210
330
240
300
270
90
5
120
60
4
3
150
30
2
1
180
0
210
330
240
300
270
90
3
120
60
2
150
30
180
0
210
330
240
300
270

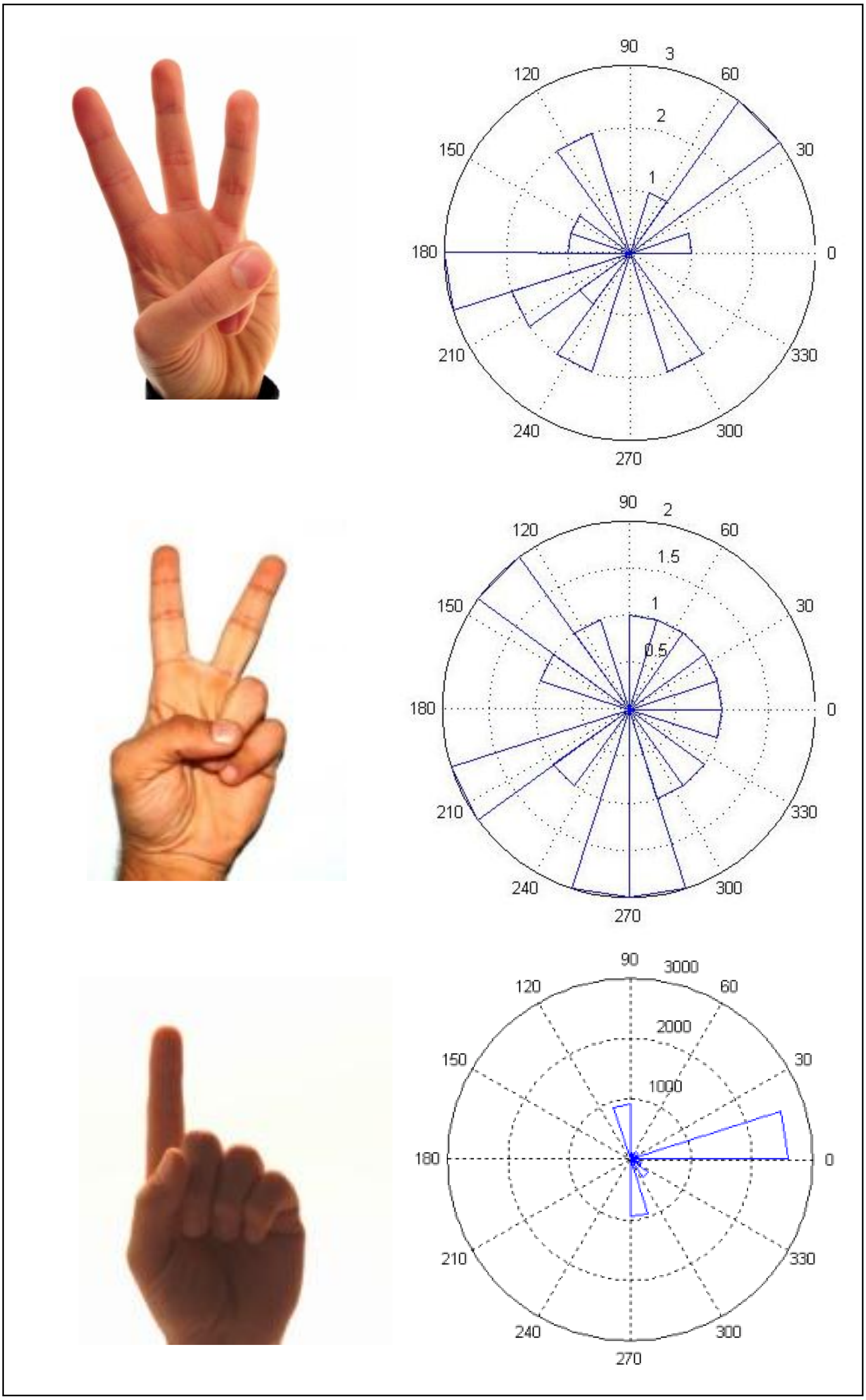


Figure 5.8: Gestures used in the system and their OHs.

As six predefined gestures are taken to test developed method, these samples would be used for training. The gesture and its corresponding OH are shown in Figure 5.8 for all six samples.

5.5 Neural Networks Implementation

Neural networks are efficient for Classification and have been used and lead to very satisfying results. The main difficulty lies in the training and all the pre- processing it requires ready. Neural networks can be used to solve some of the problems in vision for which procedural algorithms are difficult to generate and optical computing can be considered as a means to providing the greater computing power required for real time and more general- purpose vision systems [Maung 2009]. There are a variety of benefits that an analyst realizes from using neural networks in their work [Maung 2009].

a) Pattern recognition is a powerful technique for harnessing the information in the data and generalizing about it. Neural nets learn to recognize the patterns which exist in the data set.

b) The system is developed through learning rather than programming. Programming is much more time consuming for the analyst and requires the analyst to specify the exact behavior of the model. Neural nets teach themselves the patterns in the data freeing the analyst for more interesting work.

c) Neural networks are flexible in a changing environment. Rule based systems or programmed systems are limited to the situation for which they were designed, when conditions change, they are no longer valid. Although neural networks may take some time to learn a sudden drastic change, they are excellent at adapting to constantly changing information.

d) Neural networks can build informative models where more conventional approaches fail. Because neural networks can handle very complex interactions they can easily model data which is too difficult to model with traditional approaches such as inferential statistics or programming logic.

e) Performance of neural networks is at least as good as classical statistical modeling, and better on most problems. The neural networks build models that are more reflective of the structure of the data in significantly less time.

The neural network designed consists of 18 neurons at the input layer, 9 hidden neurons and 6 neurons at the output. The architecture of neural network is shown in the Figure 5.9.

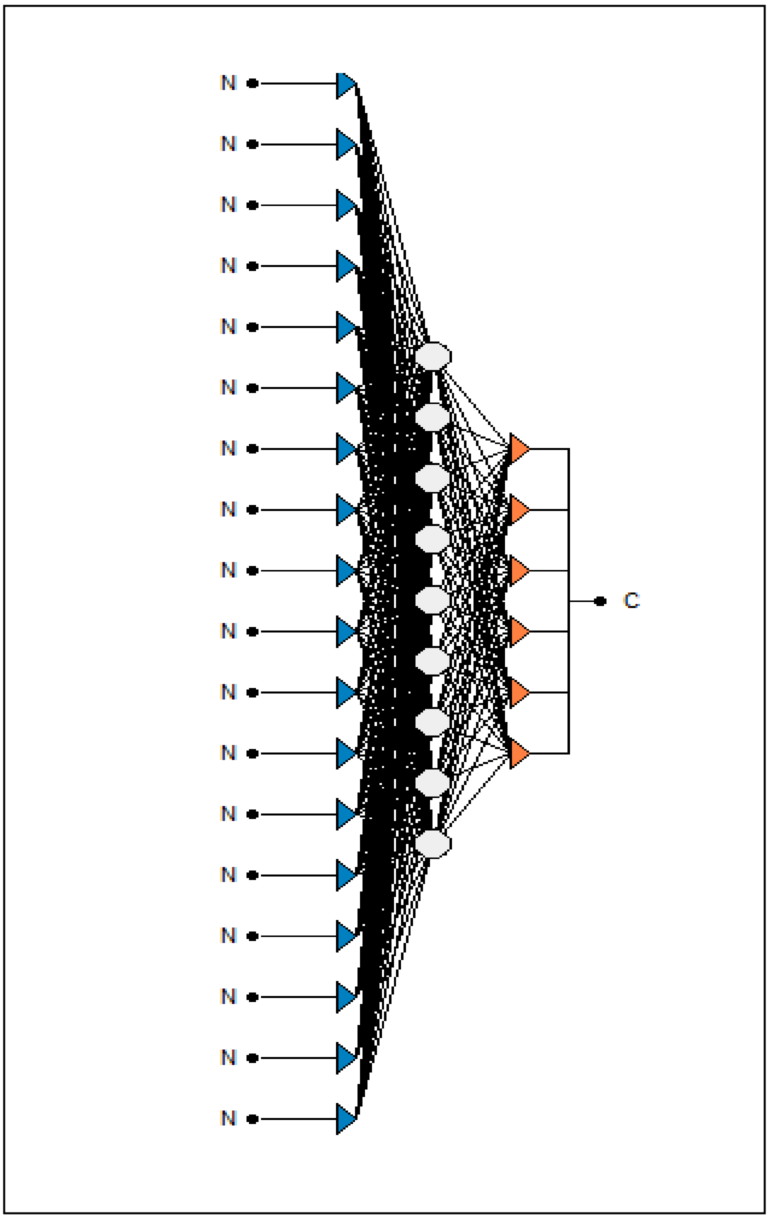


Figure 5.9: Neural Network Architecture

5.5.1 ANN Training

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature the network function is determined largely by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements.

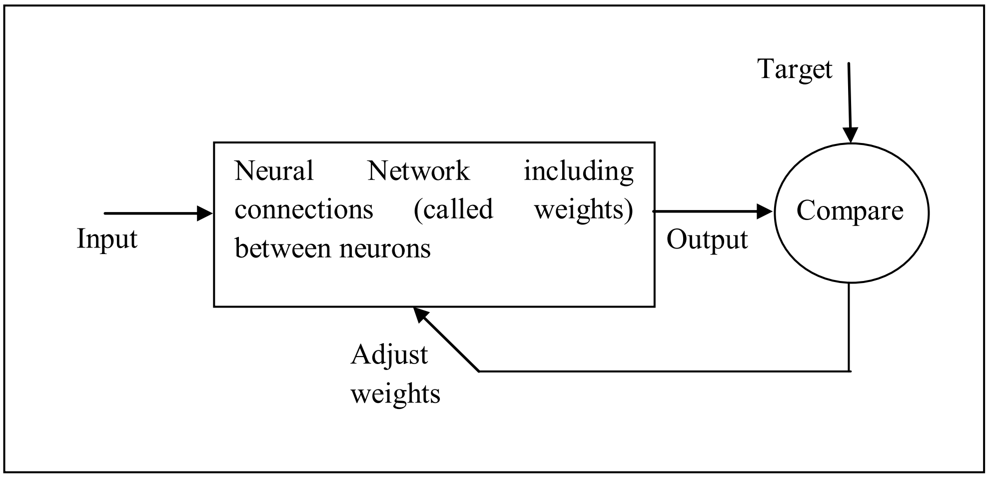


Figure 5.10: Neural Network Block Diagram [Maung 2009].

Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in Figure 5.10. Here the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning to train a network.

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, and vision and control systems. Today neural networks can be trained to solve problems that are difficult for conventional computers or human beings. The supervised training methods are commonly used but other networks can be obtained from unsupervised training techniques or from direct design methods. Unsupervised networks can be used, for instance to identify groups of data. Certain kinds of linear networks and Hopfield networks are designed directly. In summary, there are a variety of kinds of design and learning techniques that enrich the choices that a user can make. For this system supervised learning has been used while back propagation algorithm has been used for training. The process of training the network is simply a matter of altering the connection weights systematically to encode the desired input – output relationship.

5.5.2 Back Propagation Algorithm

Back Propagation algorithm has been selected since it is simple to implement and also it is a standard method and generally works well. It requires a teacher that knows, or can calculate, the desired output for any input in the training set. It is most useful for feed-forward networks (networks that have no feedback, or simply, that have no connections that loop). Back propagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable. The back propagation learning algorithm can be divided into two phases: propagation and weight update.

Phase 1: Propagation

Each propagation in the ANN involves the following steps:

1. Forward propagation of a training pattern's input through the neural network in order to generate the propagation's output activations.
2. Backward propagation of the propagation's output activations through the neural network using the training pattern's target in order to generate the deltas of all output and hidden neurons.

Phase 2: Weight update

For each weight-synapse:

1. Multiply its output delta and input activation to get the gradient of the weight.
2. Bring the weight in the opposite direction of the gradient by subtracting a ratio of it from the weight.

This ratio influences the speed and quality of learning; it is called the learning rate. The sign of the gradient of a weight indicates where the error is increasing; this is why the weight must be updated in the opposite direction. Repeat the phase 1 and 2 until the performance of the network is good enough.

There are two modes of learning to choose from: One is on-line learning and the other is batch learning. In on-line learning, each propagation would be followed immediately by a weight update. In batch learning, much propagation occurs before weight updating occurs. Batch learning requires more memory capacity, but on-line learning requires more updates. As the algorithm's name implies, the errors propagate backwards from the output nodes to the inner nodes. Back propagation calculates the gradient of the error of the network regarding the network's modifiable weights [Werbos 1994] .This gradient is almost always used in a simple stochastic gradient descent algorithm to find weights that minimize the error. Back propagation usually allows quick convergence on satisfactory local minima for error in the kind of networks to which it is suited.

Back propagation networks are necessarily multilayer perceptrons (usually with one input, one hidden, and one output layer). In order for the hidden layer to serve any useful function, multilayer networks must have non-linear activation functions for the multiple layers: a multilayer network using only linear activation functions is equivalent to some single layer, linear network. Non-linear activation functions that are commonly used include the logistic function, the softmax function and the gaussian function. The back propagation algorithm is applied for training gestures. This system is using a transformation that converts an image into a feature vector which was used to train neural network. Features were extracted from all sample images and were feed to ANN. After training, the feature vectors of a test image would be sent to this ANN for classification.

The feature vectors are scaled in the range of -5 and +5. These are applied to the neural network. The error is calculated by subtracting the output value from target value. Then the sum-squared error was calculated. The error graphs of the network training for different values are shown in Figure 5.11, 5.12 and 5.13.

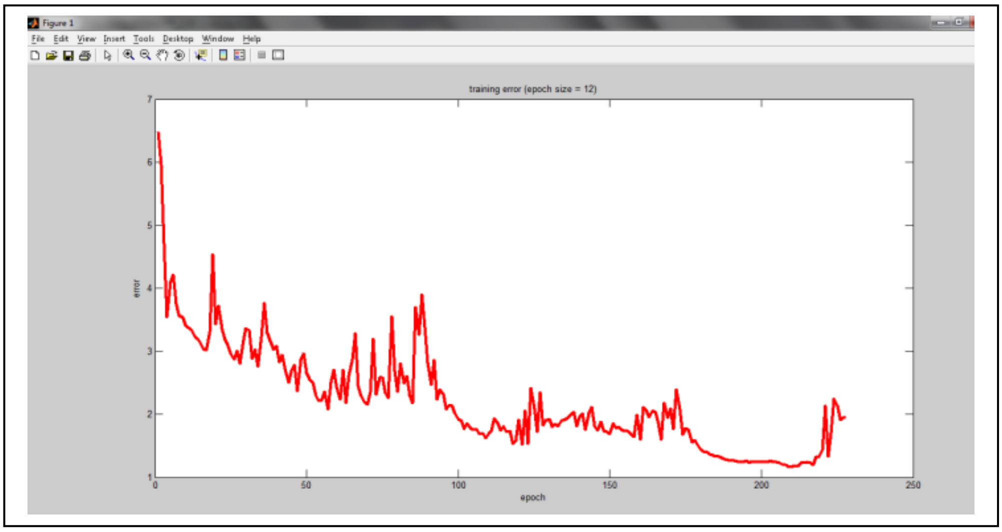


Figure 5.11: Training Error for epochs 120.

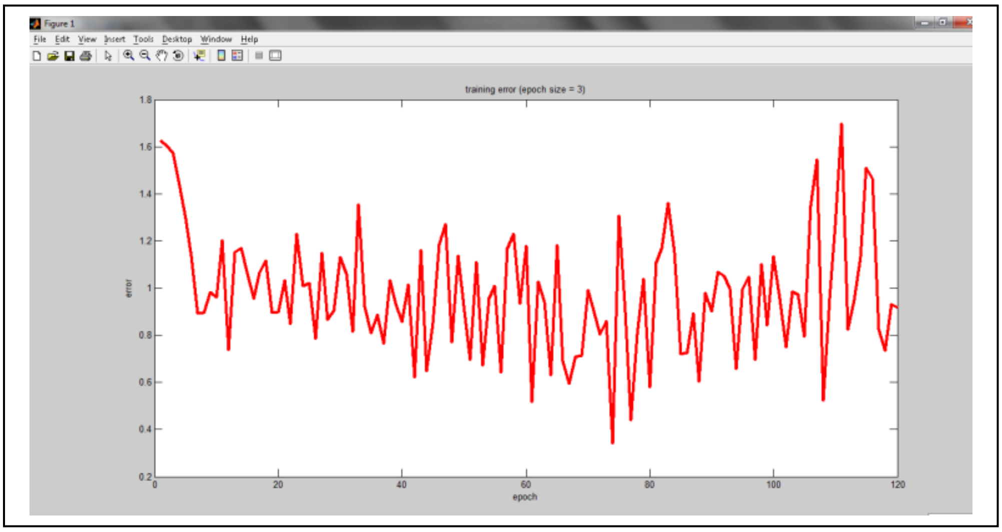


Figure 5.12: Training Error for epochs 100.

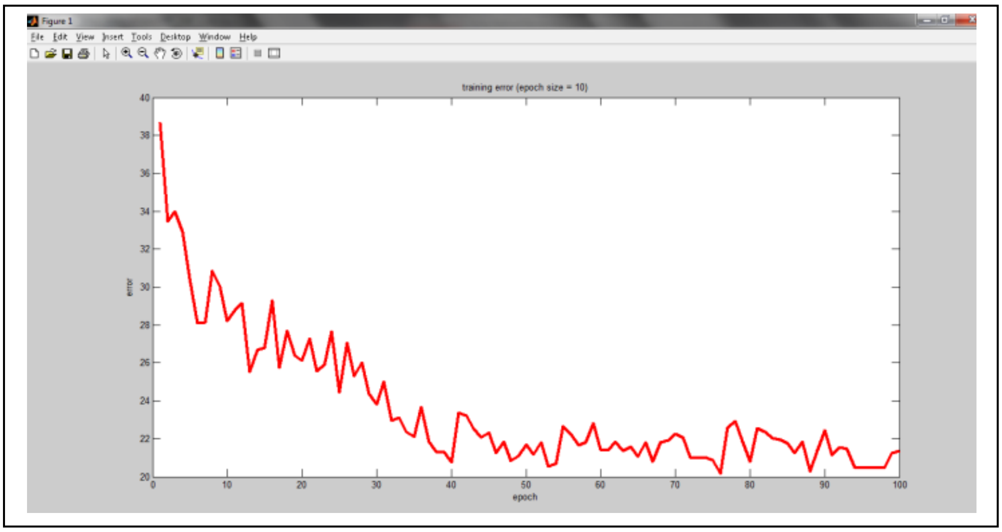


Figure 5.13: Training Error for epochs 140.

5.6 Experimental Results

The target vectors for six sample gestures are defined in Table 5.1. The gesture recognition of test image was performed with matching the images stored in database, first with Euclidean distance method and then using neural network to improve results. Euclidean method was giving satisfactory results but the false detection rates for few gestures were high.

Table 5.1: Gestures and their target vectors

Gesture	Target Vectors
	000001
	000010
	000100
	001000
	010000
	100000

Figure 5.14 shows the pre-processing results from live image frames, which was done as the procedure is discussed in chapter 4. The Euclidean distance method was applied on a varied set of images several times and the outputs obtained are tabulated in Table 5.2. It show the results of one test image with all six type of gestures stored in database. The minimum difference between two feature vectors would be considered a match. The matched gesture is shown in bold font in the Table 5.2.

Table 5.2: Euclidean Distance

S.No	**Test Image**	**Single Finger**	**Two Fingers**	**Five Fingers**	**Closed Fingers**	**Thumb up**	**Three Fingers**
1	Pattern 1	0.625	**0.435**	1.457	0.667	1.297	0.734
2	Pattern 2	3.366	3.084	**1.661**	1.974	2.597	0.346
3	Pattern 3	1.874	2.0997	2.368	2.070	**1.637**	2.254
4	Pattern 4	**0.4122**	0.593	1.810	1.644	0.834	0.700
5	Pattern 5	0.599	0.350	1.992	1.897	1.897	**0.227**
6	Pattern 6	0.3723	0.3783	0.2654	**0.23407**	0.394	0.204
7	Pattern 1	0.563	**0.367**	1.524	0.733	1.379	0.648
8	Pattern 2	3.431	3.257	**1.749**	2.697	1.943	3.628
9	Pattern 3	1.874	2.099	2.368	2.070	**0.637**	2.254
10	Pattern 4	**0.313**	0.496	2.180	1.650	2.647	3.890
11	Pattern 6	0.3527	0.3266	0.1962	**0.1850**	0.2606	0.363
12	Pattern 5	0.3174	0.3240	0.2625	0.2735	0.2450	**0.150**
13	Pattern 1	0.6094	**0.3677**	1.5240	0.7340	1.3791	0.609
14	Pattern 2	0.241	0.2596	**0.1549**	0.19562	0.17498	0.269
15	Pattern3	0.1818	0.1504	0.1662	0.1214	**0.106**	0.204
16	Pattern 4	**0.4123**	0.4777	1.8512	1.0046	1.7786	0.599
17	Pattern 6	0.3266	0.3381	0.1962	**0.1857**	0.2606	0.350
18	Pattern 5	0.4167	0.7008	2.0689	1.2571	1.9901	**0.227**
19	Pattern1	0.9133	**0.5649**	1.2087	0.75132	1.2002	0.858
20	Pattern 2	0.3257	0.3429	**0.185**	0.2785	1.934	0.355
21	Pattern 3	1.818	1.5046	1.662	1.0635	**0.2914**	2.045
22	Pattern 4	**0.4776**	1.233	1.8512	1.7786	0.5999	1.004
23	Pattern 5	0.5125	0.5013	2.0689	1.2571	1.891	**0.127**
24	Pattern 6	2.4372	3.2424	3.2793	**0.27191**	2.3341	3.554

Where pattern 1 to 6 represents two fingers gesture, five fingers gesture, thumbs up gesture, single finger gesture, three fingers gesture and closed fingers gesture respectively.

Figure 5.14: Test Image Captured at real time and output after skin filtering.

After this method, supervised artificial neural network is used for gesture classification. The outputs obtained for different test gestures shown by user to system webcam, are recognized by the developed system are shown in Figures 5.15, 5.16 and 5.17.

(a) (b)

Figure 5.15: Test I: Output after applying Recognition Algorithm: (a) Test image and (b) Image in database.

From the above output it can infer that though the lightning conditions were different in both the images, test image was correctly mapped to the required gesture as shown in Figure 5.15. Let’s see consider another gesture of closed fingers and its recognition as shown in Figure 5.16.

Figure 5.16: Test II: Output after applying Recognition Algorithm.

Similarly result for two open fingers gesture recognition is shown in Figure 5.17.

Figure 5.17: Test III: Output after applying Recognition Algorithm.

For comparison purpose, 14 different images for each gesture is applied to both methods and prepared their confusion matrix. Table 5.3 shows the confusion matrix for supervised neural network based gesture recognition.

Table 5.3: Confusion Matrix with Neural Network

Target / Test	Two Fingers	Single Finger	Five Fingers	Thumb Finger	Closed Fingers	Three Fingers
1	14	0	0	0	0	0
2	1	13	0	0	0	0
3	1	0	13	0	0	0
4	0	0	1	13	0	0
5	0	0	0	2	12	0
6	0	0	1	0	0	13

Each column in the confusion matrix corresponds to the number of images mapped to a particular gesture while each row contains total number of images applied for testing. For example, the test pattern 6 which is three fingers gesture, out of 14 testing images, 13 gestures were mapped correctly and the rest 1 gesture has been mapped wrongly as the five fingers gesture. Similarly for the single finger gesture, 13 were mapped correctly and the rest 1 was mapped wrongly to two fingers gesture. Overall with this method out of 84 testing images, 78 images were mapped correctly. The accuracy of recognition is obtained to be 92.86%.

Confusion matrix obtained for Euclidean distance method is shown in Table 5.4. The classification was done based on the Euclidean distance between the template and the testing image. Only 62 testing images were mapped correctly out of 84. The efficiency of recognition with this method came as 73.8%.

Table 5.4: Confusion Matrix with Euclidean distance

Target / Test	Two Fingers	Single Finger	Five Fingers	Thumb Finger	Closed Fingers	Three Fingers
1	10	2	0	0	1	1
2	1	9	0	2	2	0
3	1	0	12	0	1	0
4	1	2	1	8	0	2
5	0	0	0	1	12	1
6	0	1	1	1	0	11

So, the efficiency was improves 19.06% with neural network. The main advantage of using neural networks is that conclusions can be drawn from the network output. If a vector is not classified correctly, its output can be checked and work out a solution. Figure 5.18 shows the comparison between the successes with neural network and with Euclidean distance method for each gesture using bar graph. In the graph blue colour represents the number of successes with the neural network and the red colour represents the number of successes with Euclidean distance. Here gesture 1to 6 represents two finger, single finger, five finger, thumb finger, closed finger and three finger gestures respectively. This has been plotted after testing each method with 14 test images for each gesture.

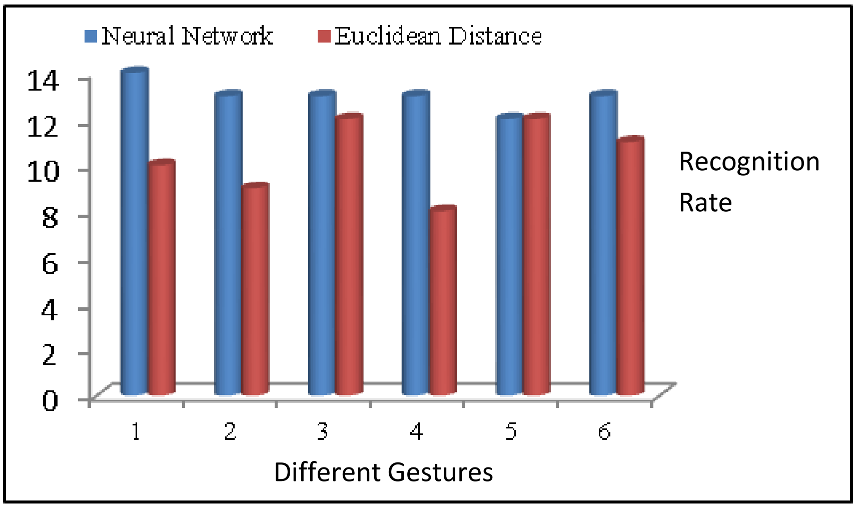


Figure 5.18: Accuracy Comparison Graph for different Gestures.

Random collected test data is applied a number of times on these two methods and collected results to get a better view of performance. Table 5.5 summarizes the collected results for each gesture.

Table 5.5: Gesture wise Accuracy Comparison

Gesture	Accuracy (With Euclidean Distance)	Accuracy (With ANN)
Two Fingers	71%	99%
Single Finger	64%	92%
Five Fingers	85%	95%
Thumb fingers	57%	92%
Closed Fingers	85%	85%
Three Fingers	81%	90%

Figure 5.19 represents Table 5.5 in line graph to show visual comparison of accuracies. The x axis numbers are gesture sequence same as shown in Table 5.5.

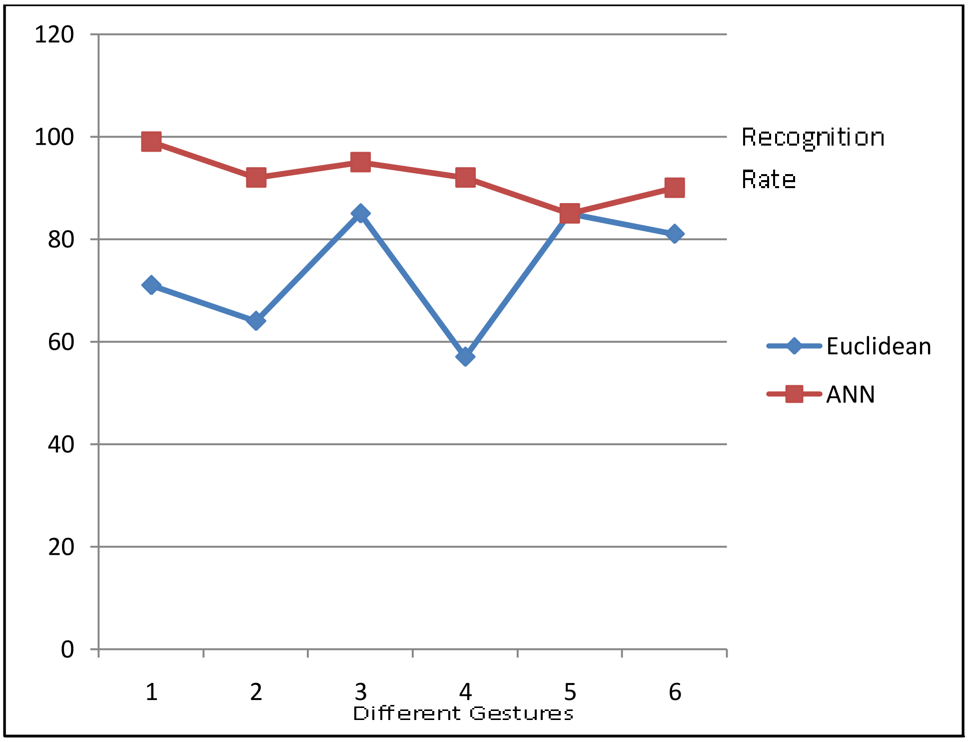


Figure 5.19: Accuracy Comparison.

5.7 Conclusion

This chapter presents a light invariant gesture recognition system which would be a great impact on current state of the art. The system is tested with Euclidean distance method and also implemented ANN with back propagation algorithm. The system can be made more robust by improving the training data set. The main advantage of using neural networks is that conclusions can be drawn from the network output. The presented method used a database of images to match with test gesture, but it's not possible to store all movements of hand. So the hand geometry needs to be identified to detect correct hand posture in image frame. Next chapter discuss about the hand geometry parameters detection from the pre-processed images which will help in HGR.

Chapter 6

Fingertips Detection

Fingertip detection forms an important component of HGR when image based models are employed for constructing or detecting hand positions. In this chapter, the focus is on direction invariant fingertip and centre of palm detection of natural hand with real time performance. The HGP is detected in 2D using a simple webcam and in 3D using KINECT. Low level image processing methods are used to detect HGP in 2D, while KINECT facilitates by providing the depth information of foreground objects. The gesture parts are segmented using the depth vector and the centres of palms are detected using distance transformation on inverse image.

6.1 Related Approaches

A number of studies have been conducted in the area of dynamic hand gesture recognition using fingertip detection. Fingertip detection should be near to real time when a video is processed. Yang [Yang & Jin+ 2005] analyses the hand contour to select fingertip candidates, then finds the peaks in their spatial distribution and checks the local variance to locate fingertips. This method is not invariant to the orientation of the hand. There are other methods which use directionally variant templates to detect fingertips [Kim & Lee 2008][Sanghi & Arora+ 2008]. Poor hand segmentation performance usually invalidates fingertip detection methods. Moreover, some of the fingertip detection methods cannot localize accurately multidirectional fingertips.

6.2 HGP Detections

HGP includes fingertips and the center of palm. In Chapter 4 the hand is segmented as a part of preprocessing. Automatic centre of palm (COP) detection in a real time input system is a challenging task, but it opens a new set of applications where hand gesture recognition can be used. This section continues with the results of segmentation from chapter 4 to detect HGP.

6.2.1 Fingertips Detection

At this point from the segmented results, one smaller image is available which contains mostly skin pixels (hand gesture shape). Since the hand direction is known, the direction of fingertips is also known. To determine all fingertips in the cropped hand image, a scan of the cropped binary image from wrist to finger ends is initiated. Consequently, the numbers of pixels are calculated for each row or column based on the hand direction, whether it is in the up-down or left-right position. Then, the intensity of each pixel is assigned values between 1 and 255 in increasing order from wrist to finger end in equal distribution. The process is presented in Figure 6.1.

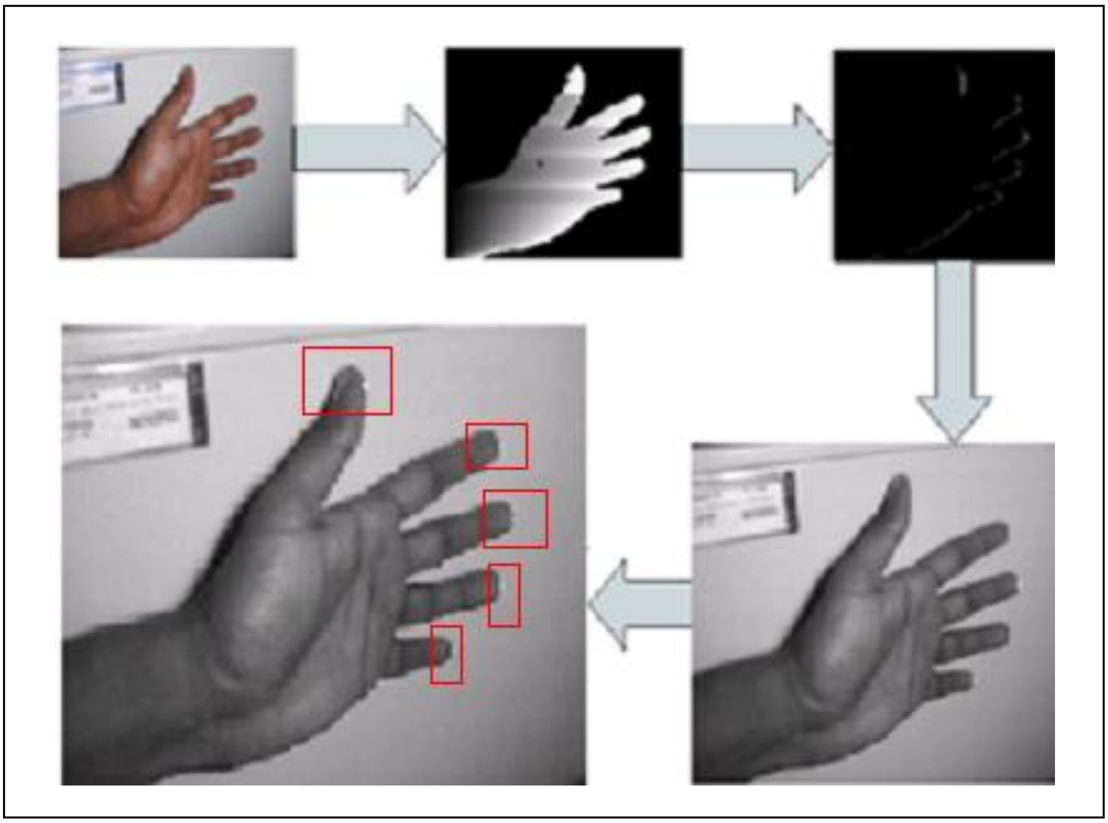


Figure 6.1: Fingertip detection process.

Hence, each skin pixel at the edges of the fingers is assigned a high intensity value of 255 as it would be the last skin pixel. Therefore, all the fingertips contain a pixel value 255 and have the brightest intensity. The fingertip detection process can be represented mathematically as

$$pixel_{count}(y) = \sum_{X=Xmin}^{Xmax} imb(x, y) \tag{6.1}$$

$$modified_{image}(x, y) = round\big(\, x \times 255/pixel_{count}(y)\big) \tag{6.2}$$

$$Finger_{edge}(x, y) = \left\{\begin{matrix} 1 \ \text{ if } modified_{image}(x, y) = 255 \\ 0 \qquad\qquad\qquad\qquad otherwise \end{matrix}\right\} \tag{6.3}$$

where $Finger_{edge}$ gives the boundary of the finger.

The line that has the highest intensity pixel is first indexed and it is checked whether the differentiated value lies inside an experimentally set threshold. If it does, then it represents a fingertip. The threshold value changes with respect to the direction of the hand. The threshold can be set after the detection of the hand direction, which is already known. For a frame resolution of 240x230 where hand direction is left to right, the set threshold is found to be 7. The enhanced results of fingertip detection are presented in Figure 6.2 where the detected pixels are marked in different colors. The fingertips have been detected in the captured frame for further operations carried out in this thesis.

6.2.2 COPs Detection

In order to determine the hand geometry with a greater precision, there is a need to detect the centre of palm in the same image. The exact location of the COP in the hand image can be identified by applying a mask of dimension 30x30 to the cropped image and counting the number of skin pixels lying within the mask. This process is made faster by employing the summed area table of the cropped binary image for calculating the masked values [Crow 1984].

In the summed area table the value at any point (x, y) is the sum of all the pixels above and to the left of (x, y), inclusive. As shown in (6.4).

$$sum(x, y) = \sum_{\substack{x' \leq x \\ y' \leq y}} i(x', y') \tag{6.4}$$

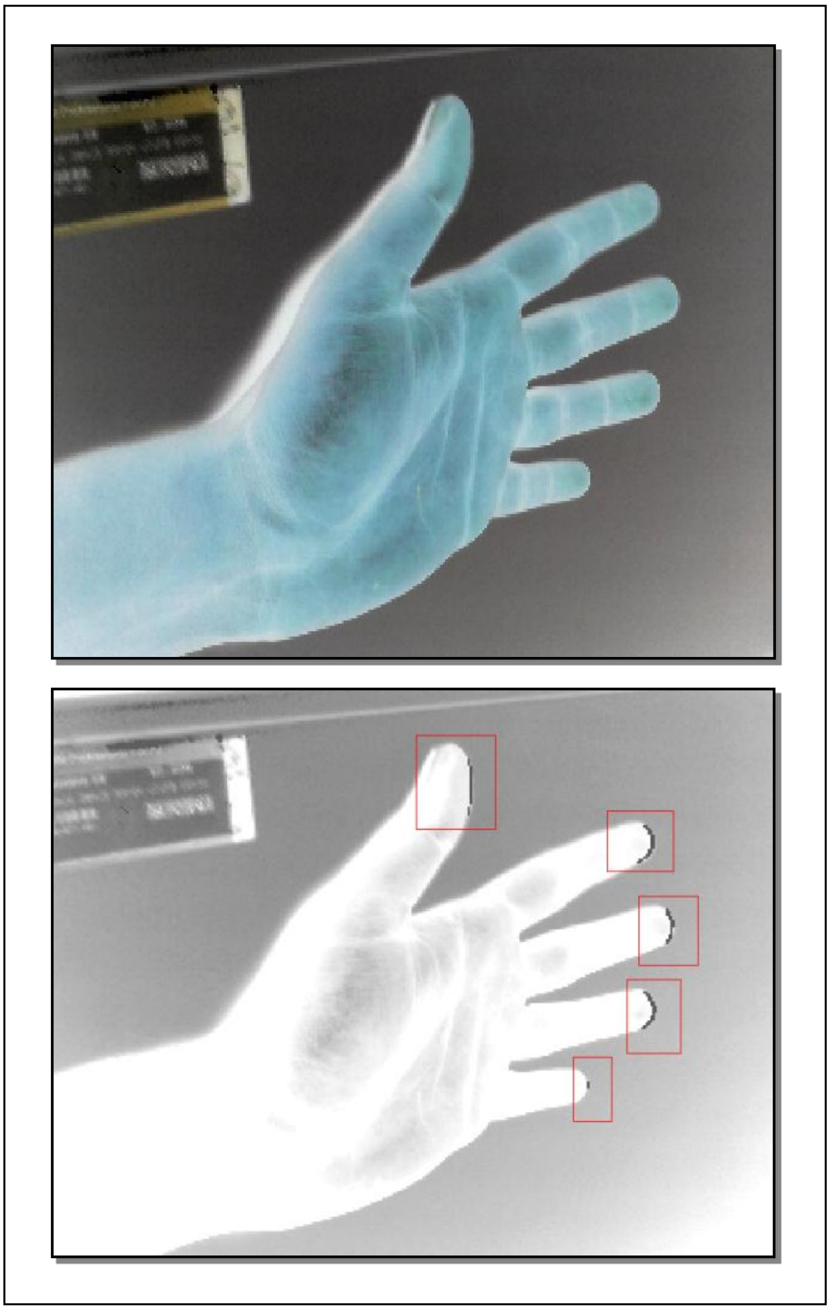


Figure 6.2: Results of fingertip detection in the original image frame.

The summed area table can be computed efficiently in a single pass over the image using (6.5)

$$sum(x,y) = i(x,y) + sum(x-1,y) + sum(x,y-1) - sum(x-1,y-1) \quad (6.5)$$

Once the summed area table is computed, the task of evaluating any rectangle can be accomplished in constant time with just four array references (see Figure 6.3) using (6.6).

$$\sum_{\substack{A(x)<x'\leq C(x)\\ A(y)<y'\leq C(y)}} i(x',y') = sum(A) + sum(C) - sum(B) - sum(D) \qquad (6.6)$$

The value of the rectangular mask over a region can be calculated by simply four lookups. This improves the speed of computation by a factor of 250. The COP is calculated as the mean of the centers of all the regions that have a sum of more than a calculated threshold, as shown in Figure 6.3.

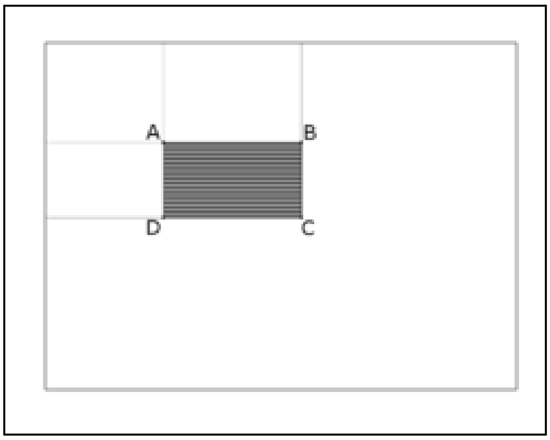


Figure 6.3: Finding the sum of a rectangular area [WIKIc].

From experiments this threshold was obtained as 832. Results of fingertips and COP detection are presented in Figure 6.4. Enhanced results are also presented in Figure 6.5.

Figure 6.4: Fingertips and centre of palm detected in a real time system.

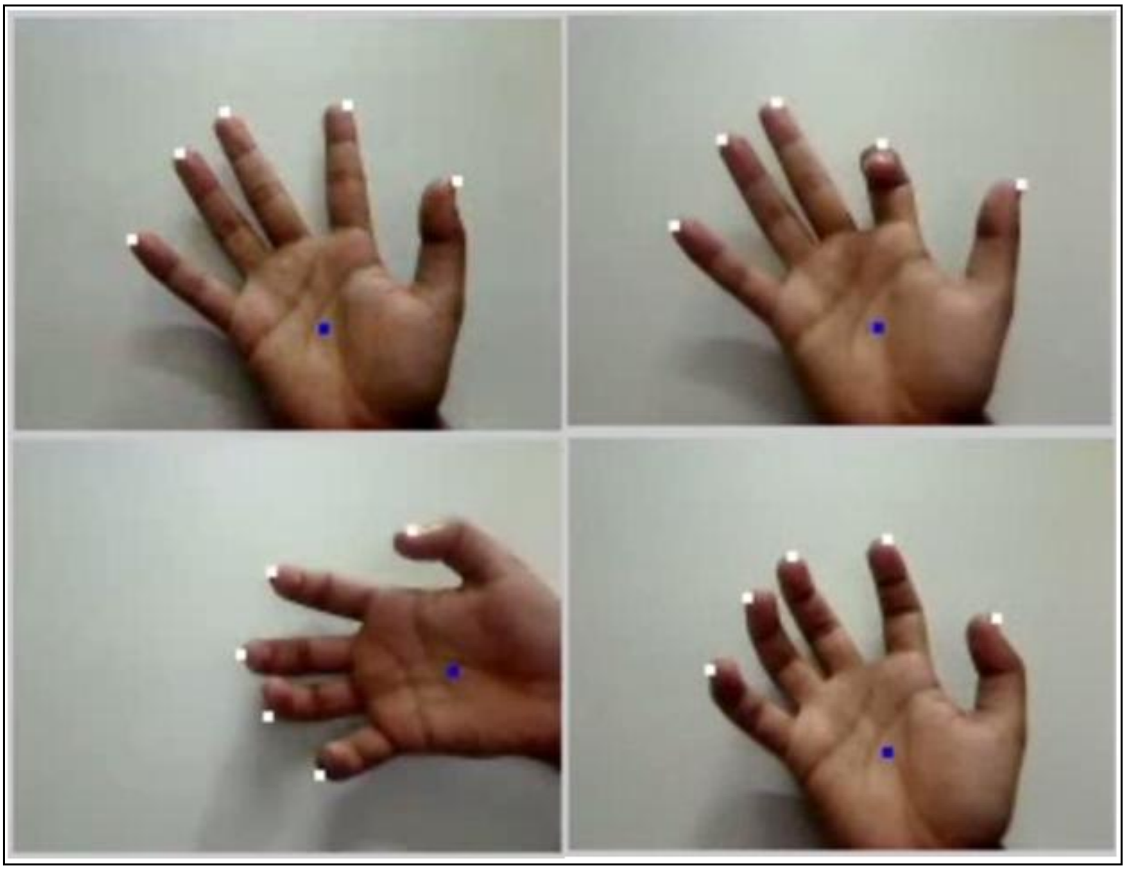


Figure 6.5: Enhanced results of fingertips and centre of palm detection.

6.3 HGP Detection using KINECT

In Chapter 4 hand segmentation was performed using KINECT. This section describes a novel method for fingertips and centre of palm detection in dynamic hand gestures generated by either one or both hands with KINECT.

6.3.1 Fingertip Detection in 3D

The approach of fingertip detection using a special device KINECT uses segmented results presented in Section 4.3.3. To detect the fingers in the ROI, first the palm of the hand is detected, which is done by applying a big circular mask to the image. Thereby all the fingers in the images are removed. Now, the palm of the hand is subtracted from the original hand image to obtain the segmented finger masks as shown in Figure 6.6. Figure 6.7 presents the result of applying the mask to the depth image collected from KINECT sensors. The resultant image consists of only fingers and then the fingertips are detected.

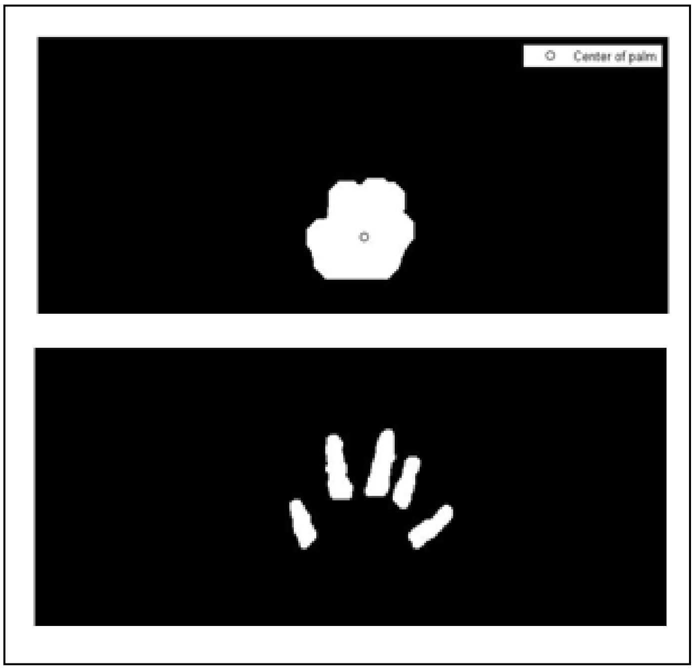


Figure 6.6: Results of palm subtraction (a) Palm in one hand image, (b) Fingers mask for one hand.

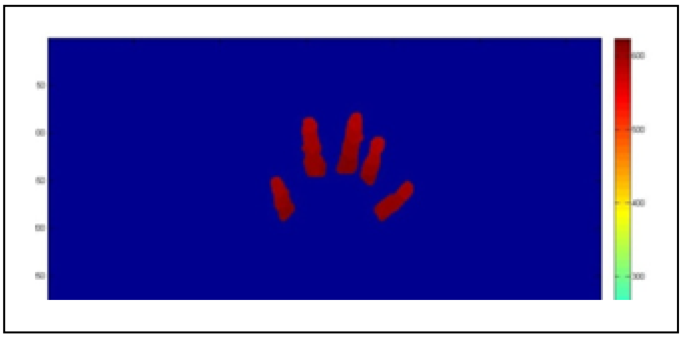


Figure 6.7: Segmented fingers in depth image.

After examining the depth map, it can be easily determined whether the value of the fingertip depth is the minimum. A minimum depth implies that the fingertips are the closest to the camera compared to the remaining objects. Thereby the fingertips are detected by determining the minimum depth in each finger. The results are presented in Figure 6.8.

Figure 6.8: Result of fingertip detection in real time.

6.3.2 COP Detection using KINECT

Centres of the palms are detected by applying the distance transform on the inverted binary images of the hand. The results are shown in Figure 6.9. It is noted that the maximum of the distance transform gives the centre of the palm on one segment.

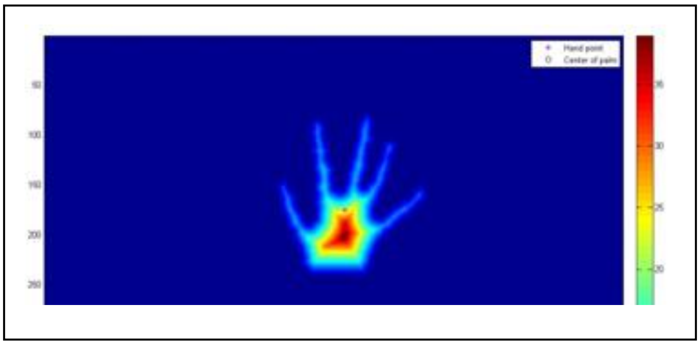


Figure 6.9: Distance transform of the hand.

6.3.3 Results

From the lab setup, fingertips and the centre of palm are identifiable very accurately even when the fingers were bent at a large angle. This is because, KINECT has nothing to do with the spatial information and this method is based on the depth information provided by the device. The accuracy for fingertips detection when all fingers are open is approximately 100%. When the fingers are fully bent, sometimes confusion is created because in this position the finger joints are closer to the device. When the centre of palm is detected results are approximately 90% accurate. The whole system is implemented based on real time requirements and the results were very encouraging (see Figure 6.10).

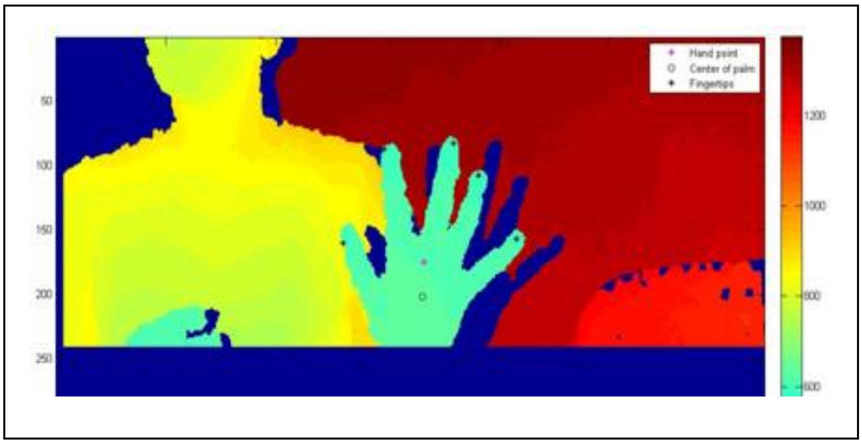


Figure 6.10: Final result showing hand point, centre of palm and fingertips.

6.4 HGP Detection for Both Hands

The fingertips and COP for one hand has been successfully detected using KINECT. The hand can be right or left, depending on whether the user is right handed or left handed. The same process for HGP detections works for both hands and can be applied simultaneously to both hands. The results obtained are very encouraging. The results for real time fingertips and COP detections for both hands are presented in Figure 6.11. The orientation of the hands is not a constraint in this approach, as the 3D sensor is able to detect hands in any direction.

As this experiment can be used for both hands, we have developed techniques for clearly distinguish between the hands. As shown in Figure 6.11, for a single hand the fingertips and the centre of palm are detected in white colour, while if both hand are detected in the image, the right hand is detected as white and the left hand is detected as pink. This colour difference ensures that the centre of palm of one hand does not match the other hand details.

6.5 Conclusion

This chapter is a milestone leading towards the ultimate goal of natural communication with machine. This chapter presents an algorithm to detect the hand geometry parameters with bare hands. The results are encouraging, specifically, 6 frames per second are processed in the MATLAB® setup, which is a significantly fast real time performance. The fingertips and the centre of palm are detected clearly with the known hand direction. Moreover, this pre-processing method is direction invariant. The user can depict the gesture in any direction and consequently the parameters are detected in that particular direction.

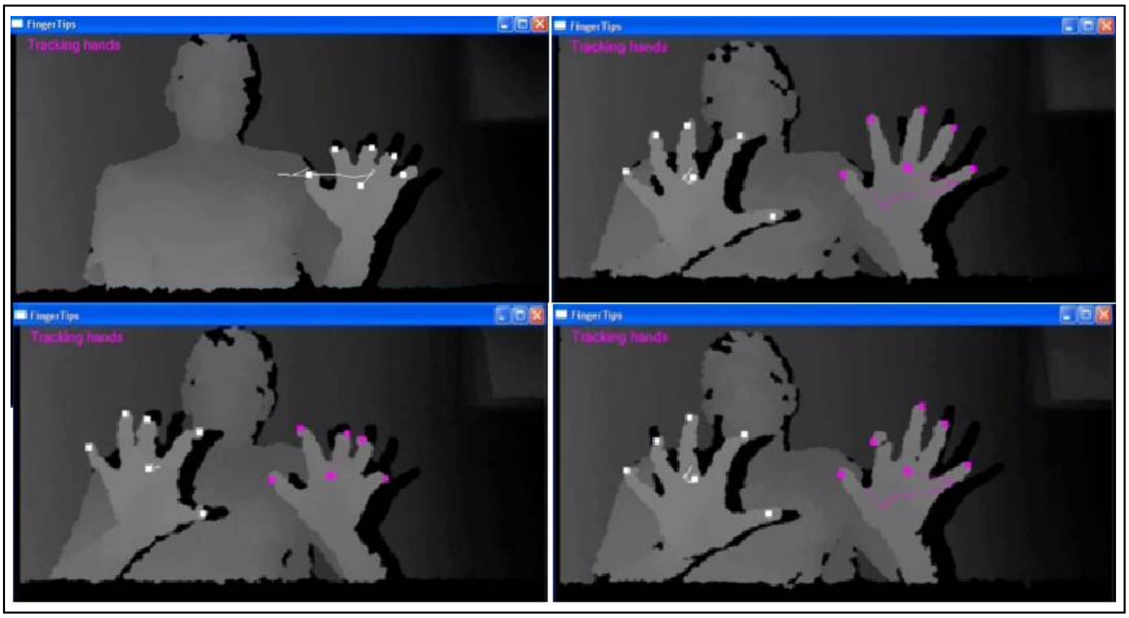


Figure 6.11: Results of fingertip detection for both hands.

The detection of fingertips and the centre of palms are also done using a special device i.e. KINECT, which satisfies all the requirements of the system considered. Using this device single or both hands can be segmented irrespective of the background and light intensity. Moreover, the results of the direction invariants are also available. KINECT is a sophisticated device that provides a number of features and it is hence significantly more expensive than a simple device such as a webcam.

HGP detection enables to get hand posture estimation which can be used in many applications. This thesis also includes controlling of a robotic hand which would mimic the hand gesture. To control robotic hand, the fingers' bending angles calculation is needed which is discussed in the next chapter.

Chapter 7

Bent Fingers' Angles Calculation

Hands play an important role in the execution of many important tasks in the day to day lives of humans as well for a number of other special purposes. The shape of the human hand is such that it is able to easily perform a number of otherwise tedious tasks. It can bend its fingers to different angles to pick up or to hold objects and to apply force via fingers or the palm area. In a number of scenarios, a human hand can perform the tasks much more efficiently than a machine shaft. This is due to the ability of a human hand to operate over a number of degrees of freedom and its ability to bend fingers at different angles.

However, in some scenarios it may not be suitable to use a human hand, while the use of a machine may be preferable. For instance, in situations like bomb detection/diffusion, execution of suspected ammunitions and landmine removal, if humans are led into the field, then casualties may occur. Hence, there is a need for a robotic hand which can perform the same operations as a human hand. The robotic hand should be able to bend fingers like a human does and it should be easily controllable. The robotic hand should have joints in the fingers, which it can bend like a human in interaction mode. Hence, in general, the robotic hand should be able to perform all the operations of a human hand in real time.

The methods presented in this chapter can be used to control a remotely located robotic hand which is able to perform the same operations as a human hand. The user shows his natural hand (without wearing any mechanical-electronic equipment) to the camera and the palm should face the camera. The behavior of human hand is detected by the camera and the robotic arm is made to operate accordingly.

This chapter describes a novel method to determine the bending angles of all fingers in the hand. The hand geometry parameters have already been determined in previous chapters. This information could be used to control an electro-mechanical robotic hand by gestures generated by the human hand. The user can show any hand to system (right of left). There is no restriction on the direction of the hand. If the palm faces the camera, the hand can be in any direction to control the electro-mechanical hand. This vision based system detects fingertips in the real time from user input and passes the information of the fingers' bending angles to the robotic hand. When the user bends his fingers to hold an object (virtual object), and the robotic hand performs the same operation i.e. holds the object. The movement of the user's hand changes the movement of robotic hand in real time.

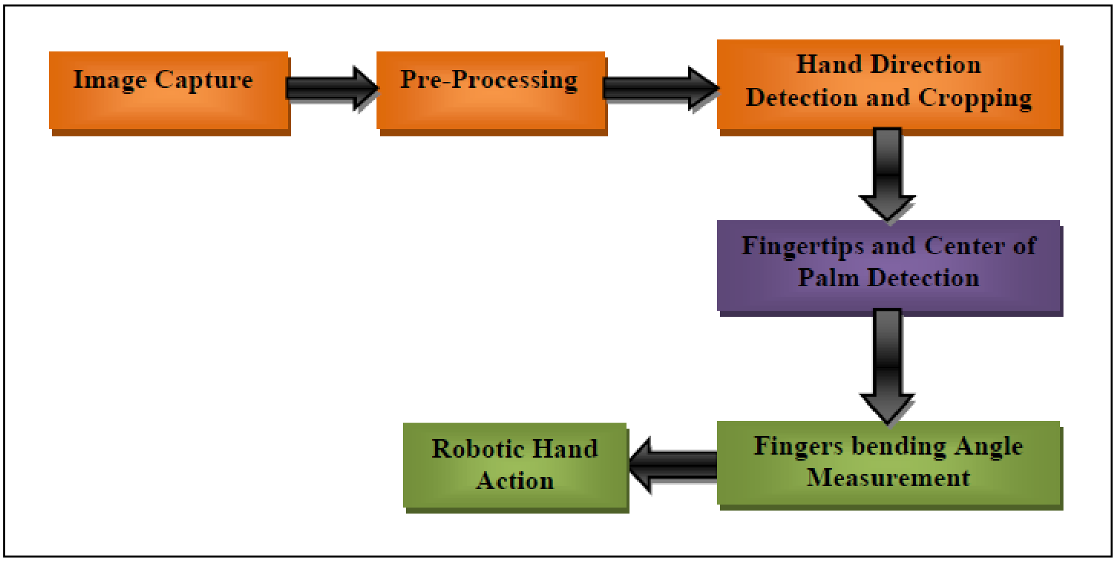


Figure 7.1: Block diagram flow of the system.

As previously discussed in this thesis, this work comes under natural computing and requires no sensors, color or paper clips to detect gestures in the image. In the past researchers have done a significant amount of work in this area, but they used a wired glove in which sensors are planted or have used colors on fingers to recognize the gesture to control robots.

The process involved in the implementation of a human gesture on a robotic hand action is described in Figure 7.1. The video captured from a webcam in 2D is preprocessed, as explained in Chapter 4 and fingertips and center of palm are detected.

7.1. Related Approaches

Many applications can be found in literature of real time robotic control in context of human-computer interaction, computer games control [Freeman 1999], human robot interaction [Triesch & Malsburg 1997] and sign language recognition [Starner & Pentland 1995][Rashid & Al-Hamadi+ 2009][Alon & Athitsos+ 2009]. Bhuyan [Bhuyan & Ghosh+ 2005] developed a gesture recognition system using edge detection and hand tracking and FSM, Trajectory guided recognition (TGR) classification techniques for developing a platform for communication with robots. Dastur [Dastur & Khawaja 2010] controlled a robotic arm by gestures recognition using the HAAR classifier. Hardenberg [Hardenberg & Berard 2001], Hoff [Hoff & Lisle 2003], Li [Li & Wachsmuth+ 2007], Man [Man & Qiu+ 2005] and Mohammad [Mohammad & Nishida+ 2009] have also used gesture recognition to control robots/electro-mechanical gadgets in their applications. Raheja [Raheja & Shyam+ 2010] controls the robotic hand using human hand movement where he uses a PCA based pattern matching.

Many researchers [Gastaldi & Pareschi+ 2005][Kim & Lee 2008][Lee & Chun 2009][Lee & Park 2009][Nguyen & Pham+ 2009][Nolker & Ritter 2002] [El-Sawah & Joslin+ 2007][Shin & Tsap+ 2004][Verma & Dev 2009][Zhou & Ruan 2006] have used fingertip detection in their research to obtain the information about the human hand according to their applications.

Very little work has been done in the area of bent fingers' angle calculation. Nolker [Nolker & Ritter 2002] presents GREFIT where she focuses on a large number of 3D hand postures. She uses finger tips in hands as natural determinant of hand posture to reconstruct the image. It takes gray scale images of 192x144 resolutions to process. Nolker uses ANN based layer approach to detect fingertips. After obtaining fingertip vectors, it is transformed into finger joint angles to an articulated hand model.

7.2. Angle Calculation

Hand Gesture based applications are mostly based on hand movements or open finger counting method. A number of research studies are currently focused on determining the number of fingers that are bent and the angles that they are bent at. Generally methods consider a partially bent finger as open and a fully bent finger as closed. However, in natural gesture positions it is not possible that the hand will remain straight and all open fingers would point upwards.

The information about the angle at which each finger is bent is can be very useful in specialized applications like remote cruise control, robotic hand control and even in unmanned military weapons. As the hand shape parameters (fingertips and centre of palm) are known, they could be used to determine the angles for the captured gesture in real time. In this section, firstly, the geometrical angle calculation method is discussed. Then, the ANN based method is discussed.

7.2.1. Distance Measurement between COP & Fingertips

The distance between each fingertip and COP can be calculated by subtracting their coordinates as shown in Figure 7.2. Here, the origin of the coordinate system is the midpoint of the wrist line. As this experiment is performed in the spatial domain, all values are the differences of pixel values. Hence, the difference is the number of pixels between the COP and a particular fingertip.

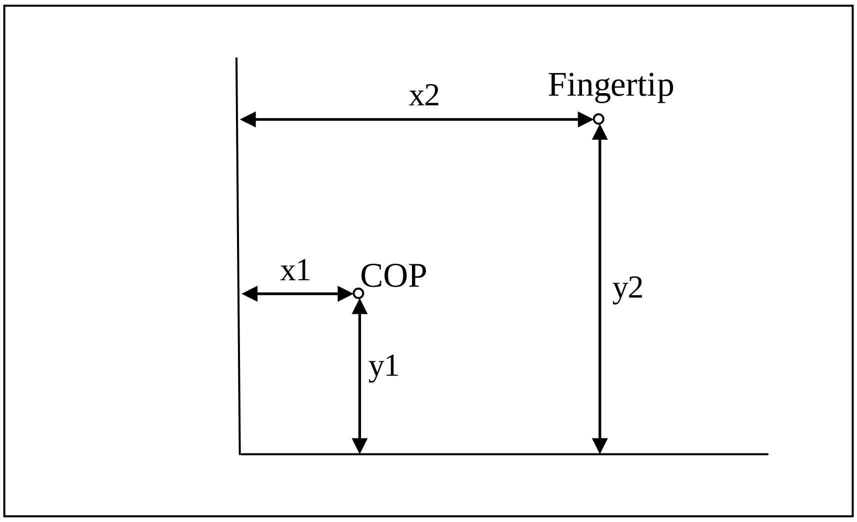


Figure 7.2: Distance calculation between COP and fingertips.

7.2.2. Fingers' Bending Angles Calculation

The process of fingers' angle calculation is very smooth. Initially the user has to show all fingers' open gesture to the system, as shown in Figure 7.3. This is recorded as the reference frame for this session. From the reference frame the initial angles are stored as 180^0 of all fingers.

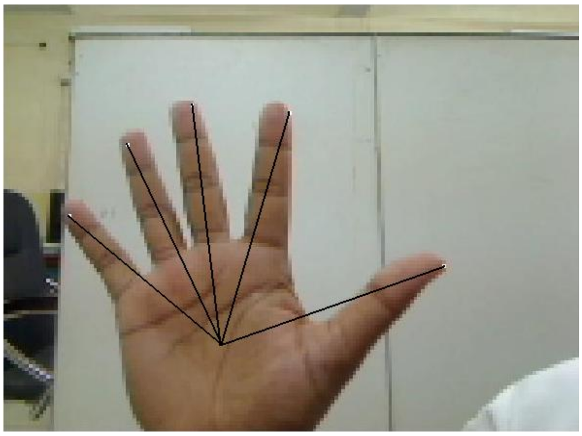


Figure 7.3: The reference frame for angle calculation.

The distance between any fingertip and the COP is the maximum in this position. As the user starts bending the fingers in either direction (forward or backward), distances among fingertips and COP start decreasing. The distance values calculated from the reference frame is stored for each finger. If the user changes the position of any of his fingers, the distance between COP and fingertips is compared with the reference distances as shown in Figure 7.4.

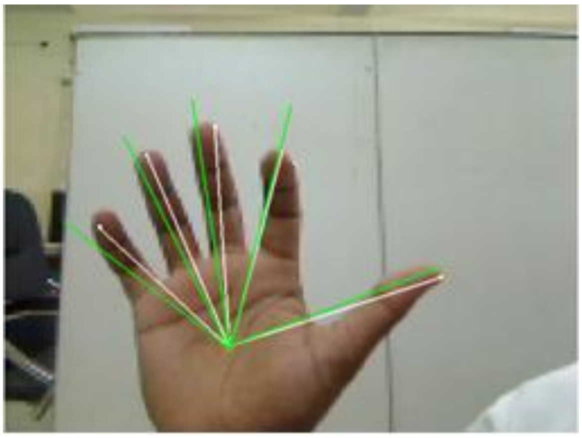


Figure 7.4: Comparisons with reference frame: Green lines show the reference distances and white lines show the current distances.

The angles for bent fingers are calculated by performing a comparison of these distances. In presented method, the angles can have values ranging between 90^0 and 180^0 as after bending more than 90^0 the base of the fingers in the hand is detected as a fingertip. Through experiments, the distance between the COP and the fingertip is assumed to be 1/3rd of the reference distance on 90^0 and when the angle is 180^0, the distance between the COP and the fingertip becomes equal to the reference distance, as shown in Figure 7.5.

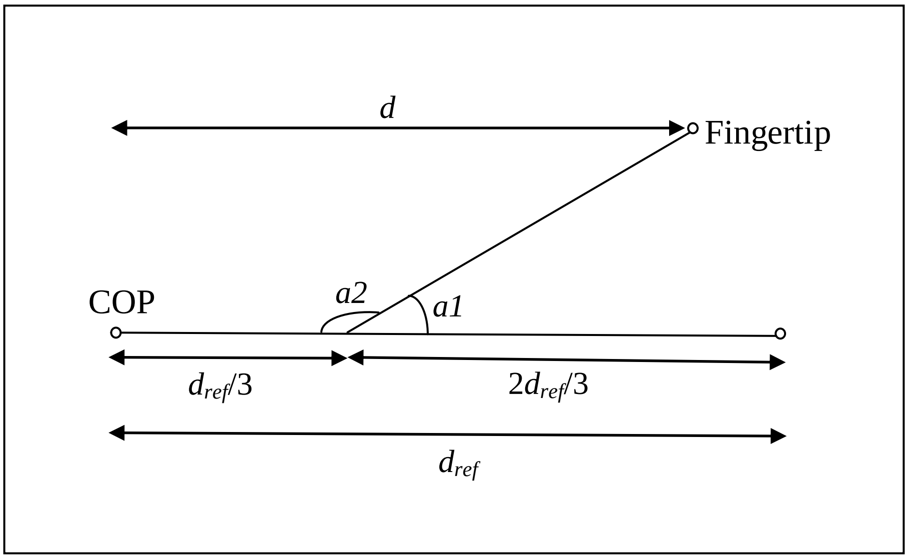


Figure 7.5: Angle approximation method.

From the Figure 7.5 it is clear that when $d = d_{ref}$, angle $a1 = 0^0$ and when $d = d_{ref}/3$, angle $a1 = 90^0$. Hence, the angle $a1$ can be expressed as

$$a1 = 90° - \frac{d - d_{ref}/3}{2d_{ref}/3} \times 90° \tag{7.1}$$

The angle of finger bending i.e. a2, which is shown in Figure 7.5, can be calculated by simple trigonometry as shown in (7.2), (7.3) and (7.4).

$$a2 = 180° - a1 \tag{7.2}$$

$$a2 = 180° - 90° + \frac{d - d_{ref}/3}{2d_{ref}/3} \times 90° \tag{7.3}$$

$$a2 = 90° + \frac{d - d_{ref}/3}{2d_{ref}/3} \times 90° \qquad (7.4)$$

In the same way bending angles for all five fingers can be calculated simultaneously. Figure 7.6 presents the results of angle detection.

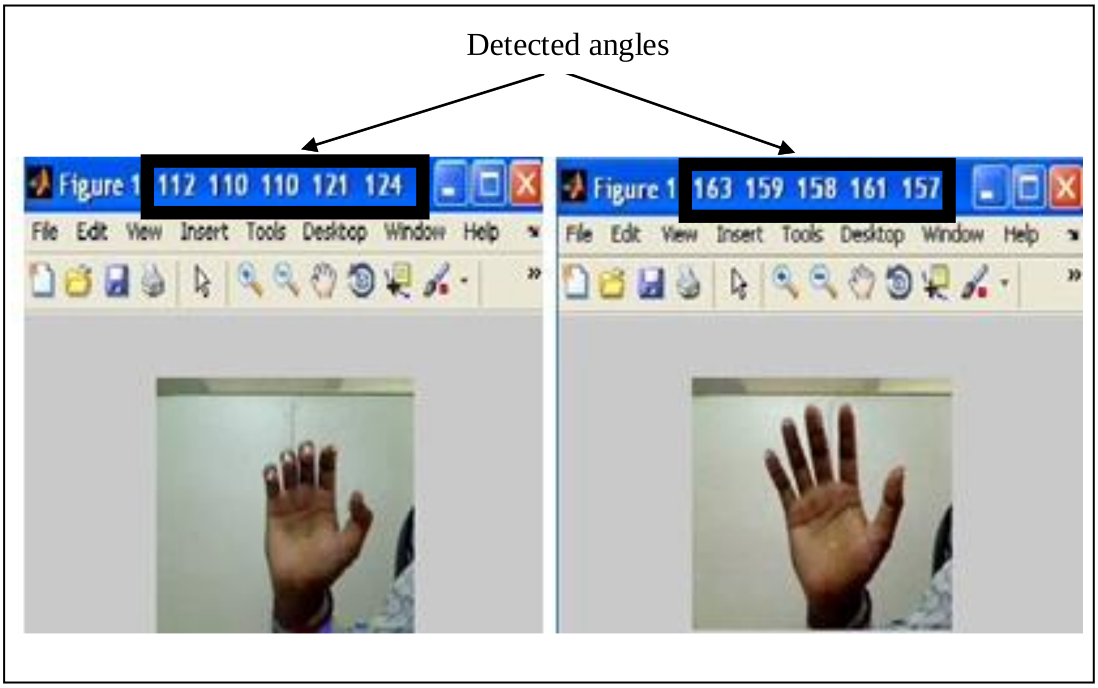


Figure 7.6:.Angle detection in one hand.

Table 7.1: Distances (number of pixels) between COP and fingertips and corresponding angles (in degrees)

S. No.	Image	Finger1		Finger2		Finger3		Finger4		Finger5	
		Distance	Angle	Distance	Angle	Distance	Angle	Distance	Angle	Distance	Angle
1. Ref		207.05	180	229.506	180	254.283	180	255.765	180	246.14	180
2.		176.78	160.3	211.32	169.3	237.103	170.9	201.479	151.3	236.24	174.6
3.		188.138	167.7	214.308	171.1	235.936	170.3	243.298	173.4	237.191	175.1
4.		125.032	126.5	192.276	158.1	199.063	150.7	206.461	154	142.302	123
5.		144.9	139.5	149.933	133.2	146.512	122.8	106.075	101	138.679	121.1

Table 7.1 presents results obtained from calculating the distances among fingertips and COP and their corresponding angles for the respective user inputs. This method works on any hand gesture input shown in any direction. Even if the user is moves the hand position, this information can also be passed to a remote robotic hand and the robotic hand would also move in the same direction. Different hand gestures and detection of hand geometry parameters are shown in Figure 7.7. It is clearly visible that hand gestures can be in any direction and the detection of parameters is robust, which is clearly visible in the image.

Figure 7.7: Fingertips and COP detections in several hand postures.

7.2.3. Performance

As a real-time system is needed to calculate the bent fingers' angle, the time taken by different components need to be measured in this system. Table 7.2 shows the comparative analysis of the time taken by the system in different steps. The simulation of the system is performed in MATLAB® running on Windows XP® and Pentium®4, 2.80 GHz processor. The image capturing frequency is configurable, currently it takes 6 images which give a feel of real time video input and calculate the fingers' position angles in different gestures. There can be varying lightning conditions, in which the user provides input to the system. The maximum time is consumed during the preprocessing stage, which is followed by image cropping and hand direction detection stage. It is clear that for the robustness of the system, there is no condition on the user. The user gives an input with his hand (one hand at a time, either right or left) in random directions.

Table 7.2: Tabulation of computational time

S. No.	Action	Time Taken (in ms)
1.	BS Formation	45(30.6%)
2.	Hand Direction & Cropping	39(26.5%)
3.	COP Detection	22(15%)
4.	Fingertips Detection	25(17%)
5.	Angle of bending	16(10.9%)
6.	Total	147(100%)

The system is tested in different conditions for a long period of time to check its sustainability in the commercial deployment and it performed excellently with different users. It is independent of the user's hand geometry and works the same for anyone. In the past Bhuyan [Bhuyan & Ghosh+ 2005] performed experiments on dynamic gestures and obtained an accuracy of 80-95%. Li [Li & Greenspan 2011] showed 88-96% accuracy for dynamic gesture recognition. Raheja [Raheja & Shyam+ 2010] obtained an accuracy of 90% in his robotic hand control work. In fact the work presented in this chapter is the first attempt towards the angle calculation in 2D under natural computing, hence there is no previous study to compare this work with. Currently system is working with an accuracy of 90-95% and we are trying to improve the system to make it more robust.

7.3 ANN Based Angle Calculation

This section discusses a novel method for the calculation of the positions of robotic fingers' angle using supervised Artificial Neural Network. User has to show a gesture to the system with bare hand as in Section 7.2.

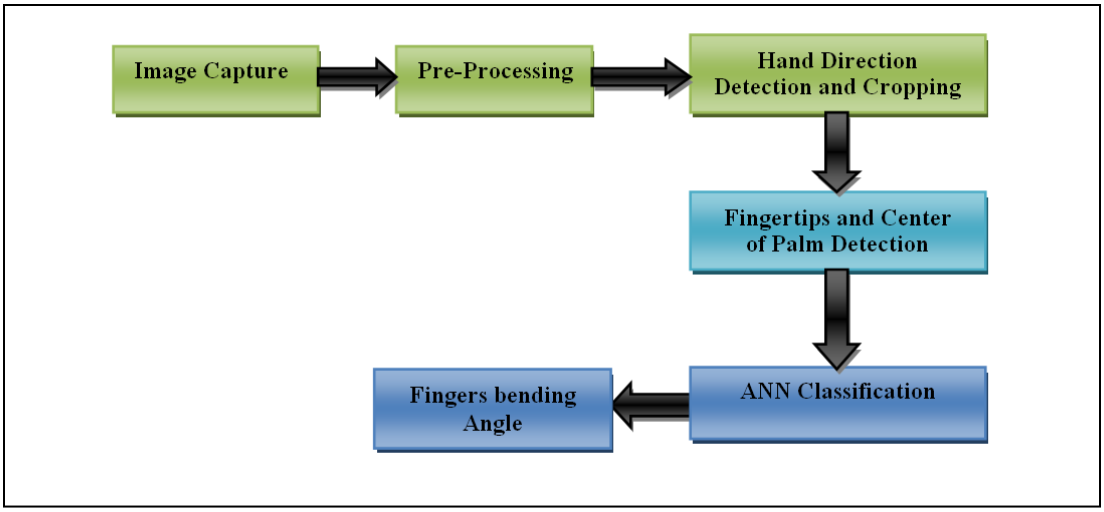


Figure 7.8: Block diagram of the angle calculation system.

7.3.1 System Description

The input to this section includes the same parameters i.e. the fingertips locations and centre of palm, which have previously been calculated in Chapter 6. The distance between the COP and fingertips has also been measured in Section 7.2.1. Here these distances are classified with supervised ANN. The block diagram of the proposed system is presented in the Figure 7.8. The ANN has five inputs for fingers' bending angle distances and five outputs for the angle for each finger.

7.3.2 Neural Network Architecture

The differences between COP and detected fingertips are obtained from each processed frame, which are the distances in pixels unit. They can be used for training the neural network. A supervised ANN is implemented using the Levenberg-Marquardt algorithm [Wilamowski & Chen 1999] with 8000 sample data for all fingers in different positions. This data is collected after storing the distances for different gestures depicted by different users and ANN is trained for 1000 iterations on this data. The architecture of ANN is shown in Figure 7.9 with 5 input layers for five finger positions and 5 output layers for the angle of each finger.

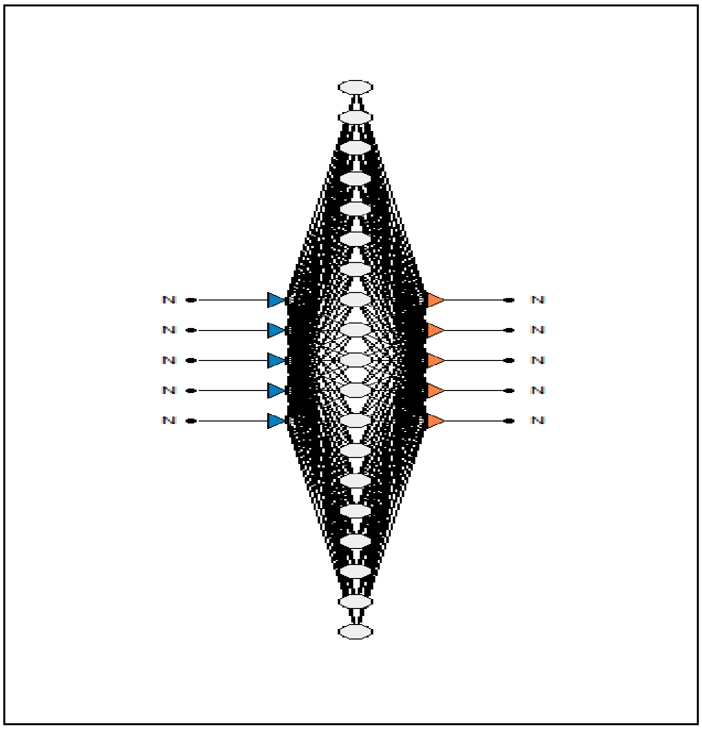


Figure 7.9: Architecture of ANN.

Table 7.3: Architecture comparison for ANN

ID	Architecture	Fitness	Train Error	Validation Error	Test Error
1	[5-1-5]	0.007762	111.6609	123.3729	128.8286
2	[5-9-5]	0.029136	21.07543	25.35231	34.32153
3	[5-14-5]	0.030816	17.03908	26.58807	32.45031
4	[5-17-5]	0.028309	22.56162	26.80747	35.32473
5	[5-18-5]	0.031086	20.17483	25.85577	32.1686
6	**[5-19-5]**	**0.037425**	**12.60105**	**22.93995**	**26.71978**
7	[5-20-5]	0.034877	12.1308	25.62003	28.67238
8	[5-21-5]	0.034308	12.13067	24.02896	29.14752
9	[5-23-5]	0.03166	14.48353	22.33495	31.5859

The system was implemented for a number of different ANN architectures and performed a comparative study. The details of different architectures considered are shown in Table 7.3. It was determined that for the 6th combination presented in the table the test error is the minimum, while the fitness values are the maximum. Hence, this is best fit for this application. The ANN design includes 2 hidden layers and 19 Neurons for processing.

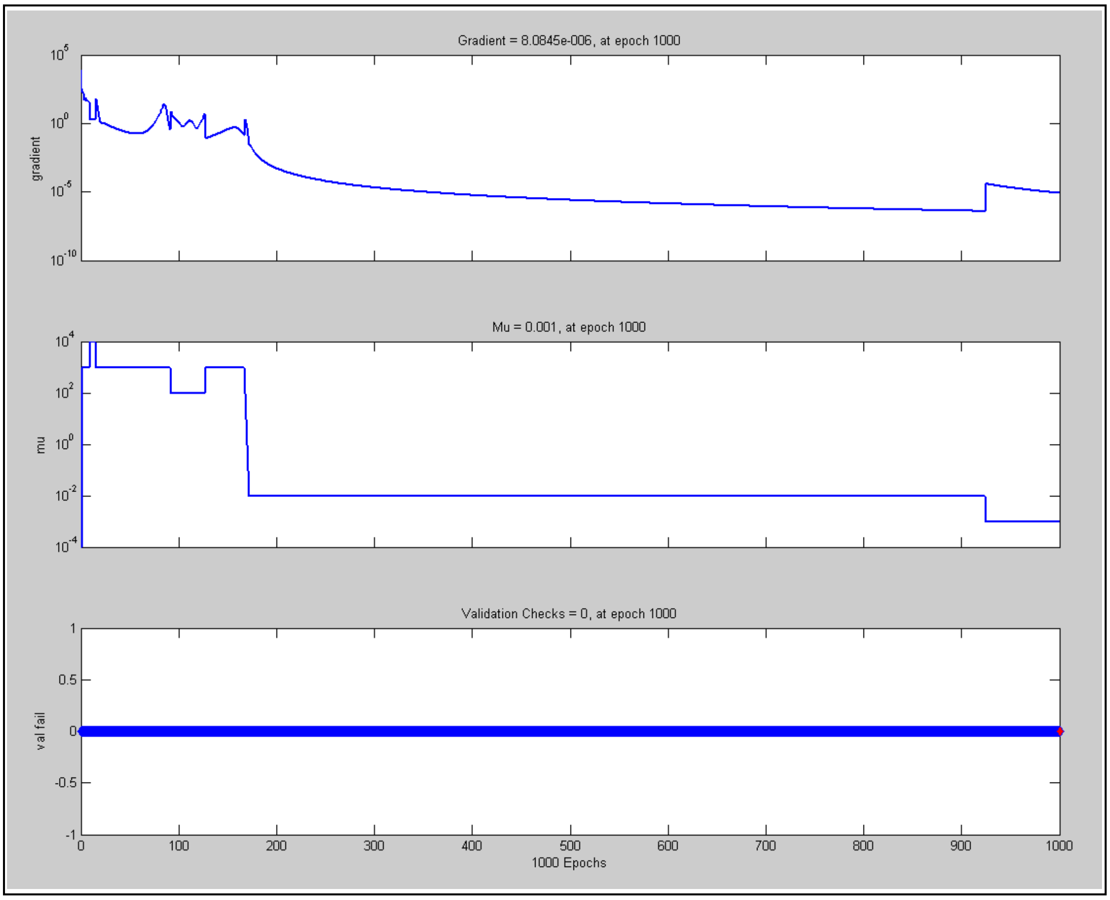


Figure 7.10: Training state using 1000 iterations.

7.3.3 Neural Network Training

A number of algorithms are available for the ANN training. The Levenberg-Marquardt algorithm is designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed-forward networks) then the Hessian matrix can be approximated as

$$\mathbf{H}=\mathbf{J}^{T}\mathbf{J} \qquad (7.5)$$

And the gradient can be computed as

$$\mathbf{g}=\mathbf{J}^{T}\boldsymbol{e} \qquad (7.6)$$

where **J** is the Jacobian matrix that contains the first derivatives of the network errors with respect to the weights and biases and **e** is a vector of network errors. The

Jacobian matrix can be computed through a standard back propagation technique which is much less complex than computing the Hessian matrix. The Levenberg-Marquardt algorithm uses this approximation [Wilamowski & Chen1999] to the Hessian matrix using the following (7.7).

$$\mathbf{x}_{k+1} = \mathrm{x}_k - \left[\mathbf{J}^{\mathrm{T}}\mathbf{J} + \mu \mathrm{I}\right]^{-1} \mathbf{J}^{\mathrm{T}} \tag{7.7}$$

When the scalar μ is zero, then (7.7) represents simply a quasi-Newton's method using the approximate Hessian matrix. When μ is large (7.7) represents a gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, hence the aim is to shift toward the Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step increases the performance function. Hence, the performance function always reduces in each iteration of the algorithm.

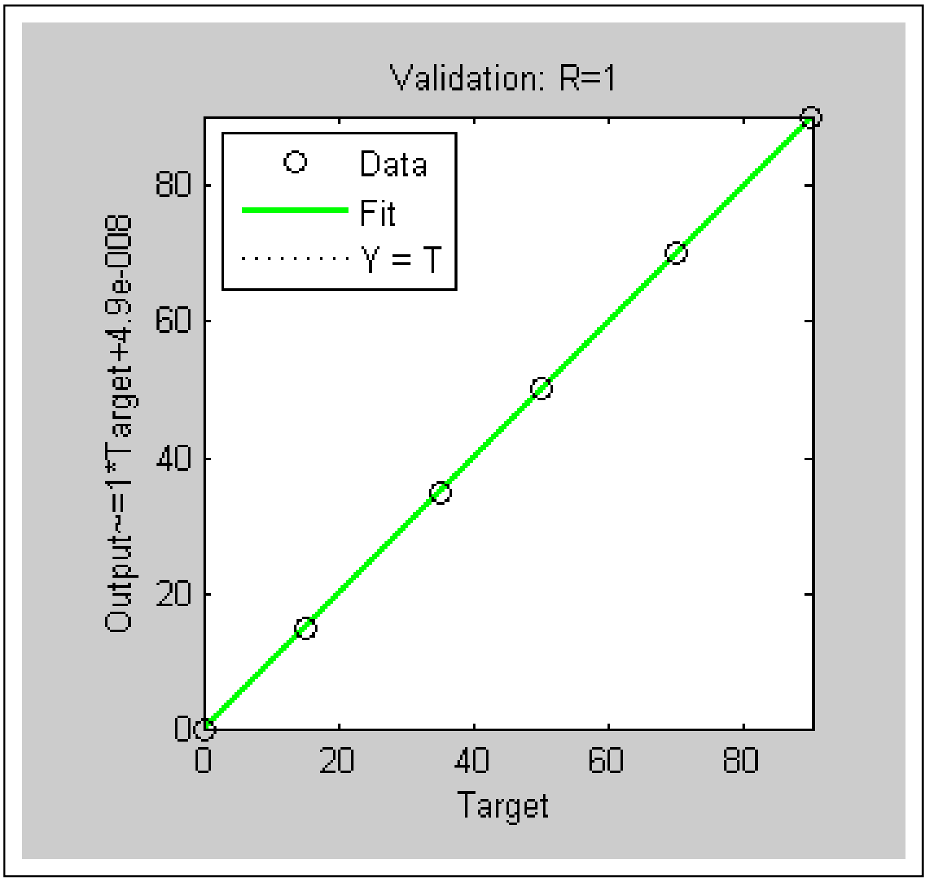


Figure 7.11: Data validation state graph.

This algorithm appears to be the fastest method for training moderate-sized feed forward neural networks (up to several hundred weights). The training state during iterations and data validation for this system is shown in Figure 7.10 and Figure 7.11 respectively. The input data includes the distances (in terms of pixels) from COP to fingertips for all fingers at different angles. Table 7.4 presents the values for one random test for all fingers. The Mean squared error in ANN is of the order of 10^{-12} as shown in Figure 7.12.

Table 7.4: Distances from centre of palm to each fingertip in pixels.

Angles	Index	Middle	Ring	Little	Thumb
0	81	87	82	75	57
15	79	84	79	70	53
30	77	80	76	67	50
45	73	72	68	64	45
60	60	63	61	60	40

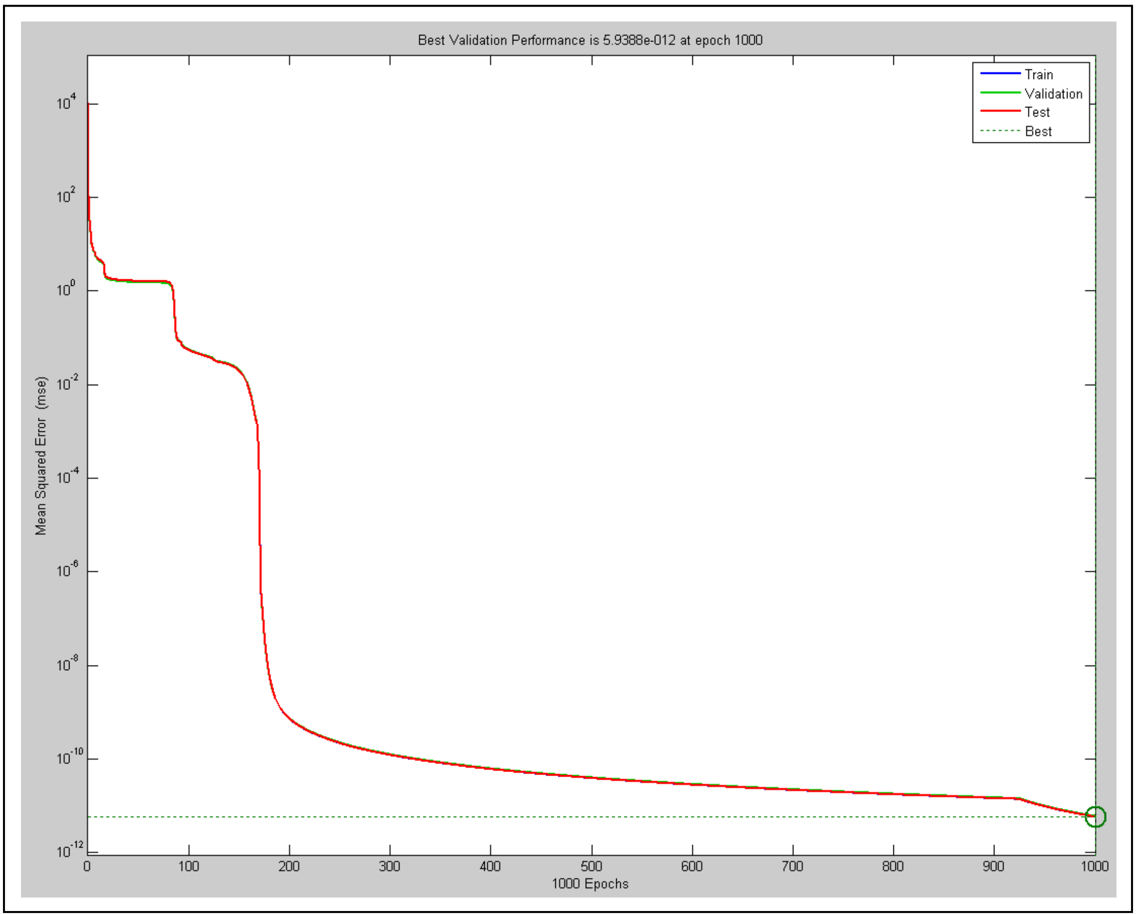


Figure 7.12: Mean squared error in the ANN.

7.3.4. Experimental Results

The ratio of the new distance in image frame to reference distance is sent to ANN to classify it and ANN provides the corresponding angles for all the five fingers. The response time of the system to display angles for one gesture is 0.001 seconds, which is very satisfactory and is close to real time. The system captures frames of 160x120 resolutions in RGB format, which is processed according to the technique previously described in Chapter 4. The reference distance is taken from the first frame of the hand and this reference distance stays the same throughout the session of system. If the hand disappears from the camera view, the system will remove the reference distance and will take the new reference distance in the same session. Hence, different users can operate in the same session. Figure 7.14 shows few snapshots of the angle calculation system.

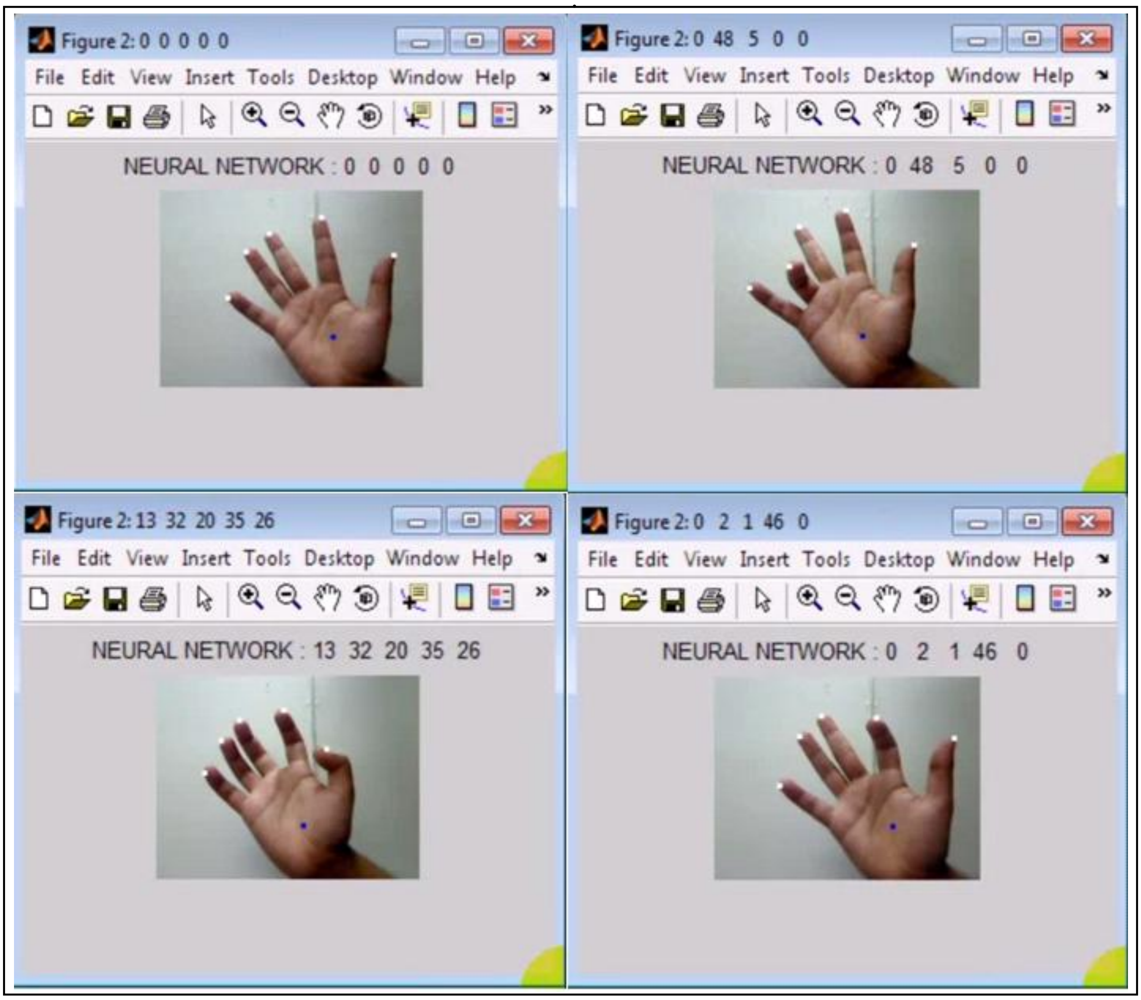


Figure 7.13: Results of fingers' bending angle computation.

The five values shown give the angles of fingers in sequence as they appear in the input image. The system takes live input from the user and calculates angles in real time. Hence, these values can be used to feed to electro-mechanical robotic hand control software so that it can do the same operation there. The simulation of the robotic hand has been done in the blender® software, where the simulated hand operates on the basis of the values provided by developed system.

7.4. Conclusion

This work presents a new research direction in gesture recognition techniques. Previously very little work has been done on closed/bent fingers detection. This chapter discusses the angle calculation process for one hand from the hand gesture shown to the system. This is done for both the right and left hand. The bending angles of fingers are calculated using a time efficient geometric modeling method and the same are obtained using ANN. The user can control the robotic hand using his gesture without wearing any gloves or markers. The results are satisfactory and this technology can be used in a number of real life applications where it is preferable to employ a robotic hand than a human hand.

As, in the real scenario, the user uses both hands together to show gesture. It is necessary to find both hands’ gesture to fulfill natural computing requirement. Also many applications need both hands to work together, so angle calculations for both hands would be required. A parallel algorithm for both hands angle calculation is discussed in detail in next chapter.

Chapter 8

Both Hands' Angles Calculation

In natural communication people use both hands to express themselves while talking. The bent fingers' angle for one hand can be detected using the method discussed in Chapter 7. There is a need to detect the angles for both hands to make the gesture based system more robust. In this chapter a novel method for angle approximation of both hands' bent fingers is presented and its application to a robotic hand control is discussed. The system uses a simple camera and a PC.

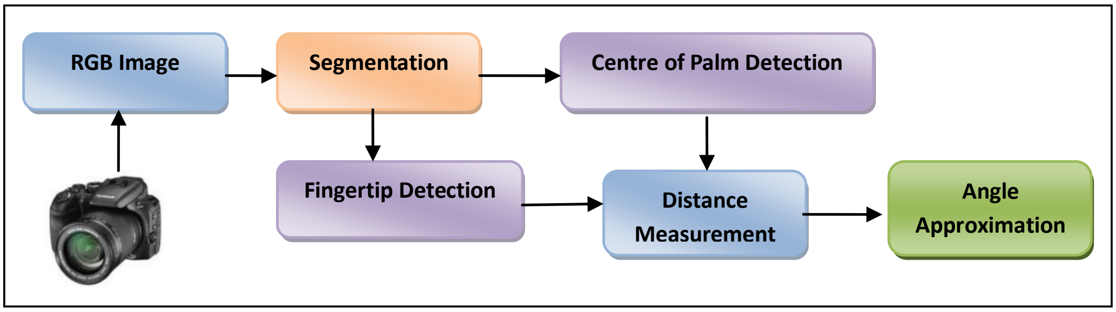


Figure 8.1: Algorithmic flow for angle calculation for both hands.

8.1 Issues

In case of both hands, it is obvious that the computational time required is greater than that for a single hand. The approach described in Chapter 7 can also be used for this purpose with some modifications in the algorithm. However, the process is time-consuming, specifically, almost twice the amount of time (for a single hand) is required when both hands are considered. It is not always true that the previous approach will consume twice the amount of time if the directions of both the hands are the same. The time consumption will be the same as that of the single hand, but in the real sense the directions of both the hands need not always be the same.

8.2 Both Hands' Angle Calculation

For calculating the angle for both hands, one option is that the algorithm (presented in Chapter 7 for a single hand) can be applied twice to the image frame. This leads to additional time consumption, which is not desirable in real-time applications. It is essential that the computational time should be less for real time performance. Hence, a new approach is developed for calculating the angle of the fingers of both hands. This approach is presented by the block diagram shown in Figure 8.1. The COP and the fingertips are detected from the segmented image and both hands fingers' angle were calculated in parallel. As for both hands, the detection process is carried out in parallel. Hence, the time consumed is smaller than that consumed when the algorithm presented in Chapter 7 is implemented twice, separately for both hands. A detailed discussion on parallel image processing is presented in [Bräunl & Feyrer+ 2001].

8.2.1. Pre-Processing

As there are two hands in the captured gesture image and it is a need now to detect both of them. For this, a change in segmentation technique is needed. The HSV color space based skin filter is used to form the binary silhouette of the input image. The hands are segmented using the same method as discussed in Section 4.2.1, where the ROI is determined. After the formation of the binary image, two binary linked objects (BLOBs) are collected and the BLOB analysis based on 8 connectivity criteria is performed. As a result of that two hands would be distinguished from each other. It is make sure that while calculating the distance between COP and fingertips, system does not make any mistake by considering the fingertip of one hand and COP of other hand. The main purpose of the BLOB analysis is to extract the two biggest BLOBs to eliminate the fault detection of skin and the skin color found in the background and to distinguish the two BLOBs from each other. Figure 8.2 presents the results for hand segmentation. The brighter BLOB corresponds to the right hand of the main frame and the other BLOB corresponds to the left hand.

Figure 8.2: Result of both hands' segmentation.

8.2.2. Fingertip Detection

The fingertip detection discussed in Chapter 7 is suitable for the simultaneously simultaneous processing of both the hands if their directions are not same. To process both hands simultaneously, a new approach is used that is based on the circular separability filter (CSF) and concentric circular filter (CCF) [Raheja & Jain+ 2010]. The CSF has the shape of a square with a disc inside as shown in Figure 8.3. After performing a number of experiments it was decided to consider the radius of the circle to be equal to 5 pixels and the bounding square to have a size of 20 pixel length.

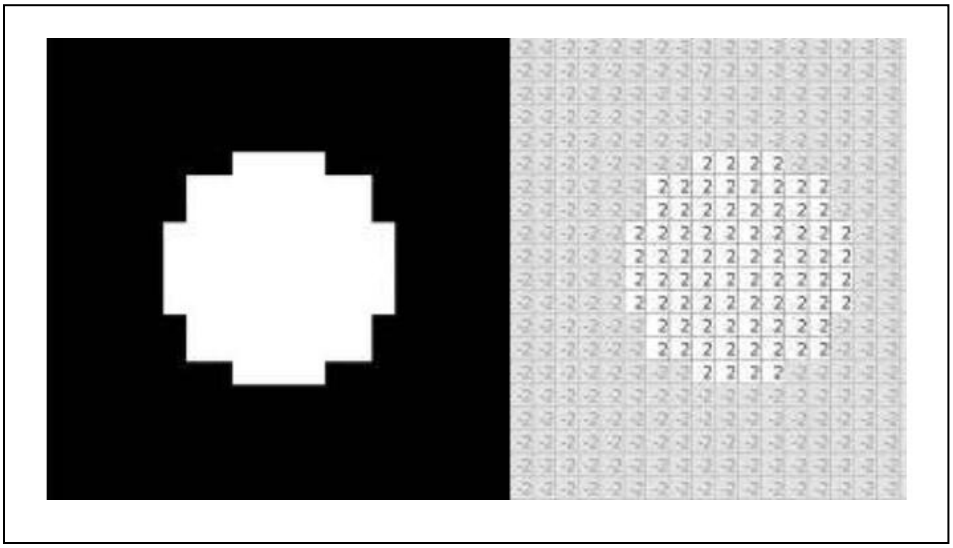


Figure 8.3: Circular separability filter.

After applying the filter on the ROI, the filter response is computed for all the points of the ROI in the binary image. The filter responses for the fingertip regions are found to be distinctively different from that of other regions. The candidate fingertip locations are determined by using an appropriate threshold condition.

The exact fingertip location is calculated in two steps. First an approximate location for the fingertip is determined and then the exact location is calculated by further calculation using the orientation of the finger. The 8-connected points that satisfy the threshold condition for the filter response of the CSF are grouped together. The groups that have a number of pixels greater than a set threshold are selected and the centroids of the groups are taken to approximate the fingertip position.

For the exact fingertips location, the orientation of each finger is determined using a filter with 2-concentric circular regions. The CCF is shown in Figure 8.4. The diameters of the inner and outer circular regions of the filter are 10 pixels and 20 pixels respectively. The points inside the inner circle are assigned a value of +2, the points outside the inner circle but inside the outer circle are assigned the value -2 and the points outside the outer circle but inside the bounding square are assigned the value 0.

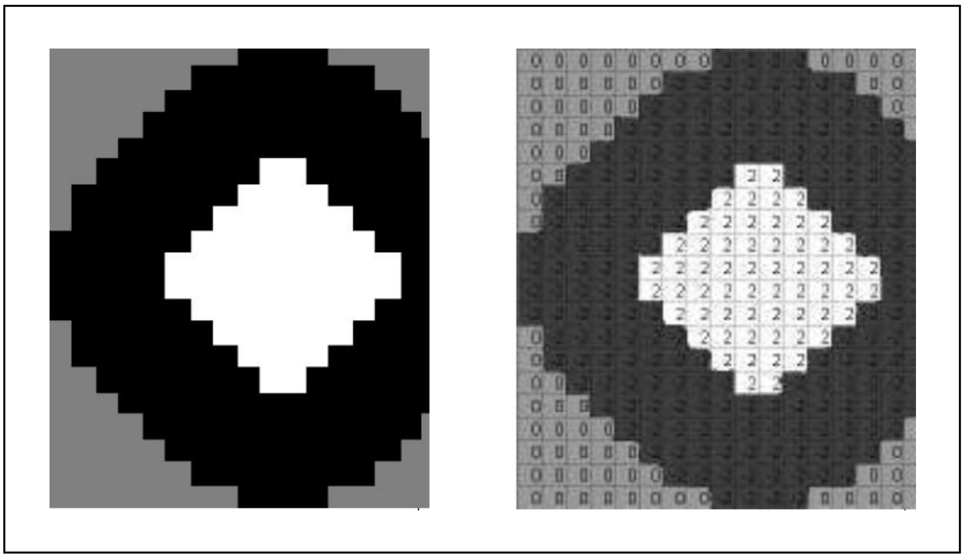


Figure 8.4: Concentric circular filter and assigned element values.

The filter is then applied to the binary silhouette of the hand image at the previously detected approximate finger tip locations. The pixels that lie in the -2 region are grouped under the 8-connectivity criteria. Then, the largest group is selected and the centroid of the group is calculated as previously discussed. The orientation of the finger is calculated as the angle (say θ) made by the line joining the centroid of the largest group and the previously calculated approximate finger tip location with the horizontal axis. This is graphically shown in Figure 8.5.

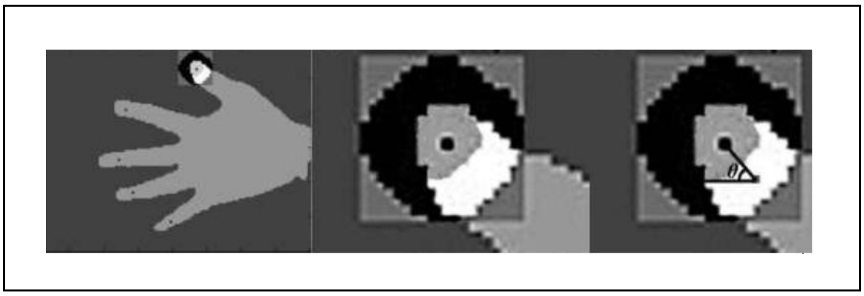


Figure 8.5: Fingertip detection (a) CCF applied on the approximate thumb tip location (b) Zoomed view of the thumb tip region (c) Position of the centroid of the largest 8-connected group (region in white) and the angle (θ) with respect to the horizontal.

After moving several steps in this direction with an incremental distance (say r) using (8.1) till the edge of the finger was reached.

$$R_{new} = R_{old} + r\cos(-\theta) \tag{8.1}$$

$$C_{new} = C_{old} + r\sin(-\theta) \tag{8.2}$$

where R_{old} and C_{old} are the 2D coordinates of the previous trace point while R_{new} and C_{new} are the 2D coordinates of the current trace point. The values of R_{new} and C_{new} obtained after performing a few iterations provide the exact coordinates of the fingertips. The results of fingertip detection are presented in Figure 8.6 by white points.

Figure 8.6: Result of both hand COP and fingertip detection.

8.2.3. Centre of Palm Detection

Centre of Palm (COP) detection is performed based on the same approach as discussed previously in Chapter 6. The exact locations of the COP in the hands are identified by applying a mask of dimension 30x30 to the binary silhouette of the image and counting the number of pixels lying within the mask. If the numbers of pixels are within a set threshold then the centre of the mask is considered as the nominee of COP and finally the mean of all the nominees found in a BLOB is considered as the COP of the hand represented by that BLOB. Since there are two BLOBs, results contain two COPs identifying the COP of both the hands. Figure 8.6 presents the result of COPs detection as yellow dots.

8.3. Angle Calculation

Here is the extension of the approach described in Section 7.2.2 to determine the fingers' angles in both hands. This geometrical method does not require any training or data to calculate the angles for both hands. The distance between each fingertip and the COP can be calculated by subtracting their coordinates as discussed in Section 7.2.1. Initially, the user has to show a reference frame to the system in which all fingers are open and the bending angle of all fingers are 180^0. The user can move his hands in front of the camera as it is not necessary to have his hand and/or arm static. The method would also calculate the angles in such a scenario.

The method given in Section 7.2.2 is based on trigonometry and performs a comparison between a reference distance and the new distance. For both hands, measure the distances between the COP and the fingertips and then using the analysis from Chapter 7, the bending angel (say *a2*) can be calculate as described is (8.3). For more information about the trigonometric concepts see Figure 6.5.

$$a2 = 90° + \frac{d - \frac{d_{ref}}{3}}{\frac{2d_{ref}}{3}} \times 90 \qquad (8.3)$$

where the angle *a2* approximates the value of finger bending angle. Figure 8.7 shows the result of fingers' angle detection for both hands. The angles are shown at the top of the window according to the finger shown sequence from the first to the last one as they appear in the captured image frame.

8.4. Experimental Results

The method uses no training data and both the hands can be oriented in any direction. The usage of the system is very similar to that discussed in Chapter 7. The experimental environment is based on Intel® i5 processor and 4GB RAM desktop computer. The discussed method is implemented in MATLAB® on Windows® XP.

The live video is captured using Logitech® HD webcam with image resolution 240x230. If single hand finger's angle calculation method is applied to detect both hands fingers' angle, the computational time is 294ms. On the other hand, the method proposed in this paper takes only 198ms to perform the same computations. Both the hands are recognized distinctly, as the system remembers both hands' parameter separately. If there is only one hand shown, system will work perform a single hand gesture analysis. This method provides an accuracy of around 90-92% on live input in different light conditions.

Figure 8.7: Finger bending angle Calculation of double hand.

8.5. Conclusion

This chapter presents a novel technique for the detection of the angles defining bent fingers in human hands. The technique presented in this paper carries tremendous significance since it can be adopted for identifying human gestures, which are often depicted during communication using both hands. The system considered uses no training data and the hands can be used in any direction. This approach minimizes the processing time of the last presented algorithm for determining the angles of a single hand. The processing time is reduced by 96 ms, which corresponds to a reduction of approximately 33%.

This thesis has presented issues from literature survey and discussed the light invariant technique for gesture recognition. Also for the controlling of robotic hand, angles from the human hands are also calculated. The conclusions of this work are presented in next chapter.

Chapter 9

Conclusions and Future Work

The prime aim of this thesis is to enhance the current state of the art of bare hand gesture recognition and presenting a model for controlling an electro-mechanical robotic hand. The focus is on the development of intelligent techniques applicable to the spatial domain for processing where user has no limitation on hand direction and will not use any extra material. The light and direction invariant methods for hand gesture recognition were investigated which provide natural comfort to user. Also the controlling of robotic hand using natural hand gives a feeling of virtual hand to the user and it is much better way than entering values of finger bending angles.

The introduction of research area and problems were discussed in chapter 1. It gives a brief about the gesture recognition process and its effectiveness with real time constraints. The goals for this research work are defined in chapter 2. Current state of art in context of natural computing is reviewed in chapter 3 where different intelligent and soft computing based HGR techniques are described. The latest results in real time performance are also given. It is also shown that current method detect only open fingers efficiently while bent fingers are either not counted or methods ignore them.

The pre-processing is discussed in chapter 4 where ROI is getting extracted from the image frame and image would be cropped. The reduced size image would make the further process faster than before. ROI segmentation is also shown using specialized device MS KINECT®, where depth information is used for gesture detection. The hand gesture recognition is explained in chapter 5, which demonstrates light invariant gesture recognition. Few gestures were already selected for the system and their OH was compared with the test image ROI to classify the gesture. The results are encouraging as in two very different lighting conditions, gestures were identified correctly. Gesture classification was done using Euclidean distance and using ANN. The ANN implementation gave better results and false positives were less.

Chapter 6 explains the process of HGP detections using webcam and KINECT. The fingertip detection is direction invariant in both conditions, user is free to show the hand in any direction. The COP using webcam was detected using sum of area method while using KINECT it was detected after applying inverse transformation on ROI depth image. If user is showing both hand simultaneously, in that case also these methods are effective and could be used to get both hand HGPs.

After detecting HGPs, the angles for bent fingers are needed to calculate. Chapter 7 describe it first using a geometrical method and later using ANN implementation. The performance analysis is also given for both approaches. These angles could be passed to a robotic hand to mimic the human hand gestures. This chapter considers only one hand operation either right or left, where chapters 8 discuss what if both hands are shown by user. A new concurrent fingertip method was applied to reduce computational time. The simulation was performed on MATLAB® and Windows XP® running on Intel i5 series processor. The approach described in chapter 6 was modified to minimize the processing time of algorithm. If the same fingertip detection algorithm is applied, it will take 294 ms to compute; whereas the new approach takes 198 ms only. Accuracy of system is around 90-92%.

Future Work

Further investigations in the area of HGR would include closed finger detections and motion invariant methods. Although KINECT is able to detect closed finger positions with few constrains but using simple devices it is still to achieve. This thesis is focused on spatial domain analysis, someone can also investigate these issues in frequency domain or model based approaches. The performance on real time embedded system is still a big issue as the cameras are going to have high resolution, more pixels are need to process in spatial domain. The processing power and memory is increasing with camera resolution but methods to minimize these latencies should be investigated.

References

[Ahmad & Tresp 1993] S. Ahmad and V. Tresp, "Classification with missing and uncertain inputs", in *Proceedings of International Conference on Neural Networks*, Amsterdam, Netherlands, vol. 3, pp. 1949-1954, 1993.

[Alon & Athitsos+ 2005] J. Alon, V. Athitsos, Q. Yuan and S. Sclaroff, "Simultaneous localization and recognition of dynamic hand gestures", in *IEEE Workshop on Motion and Video Computing*, vol. 2, pp. 254-260, January 2005.

[Alon & Athitsos+ 2009] J. Alon, V. Athitsos, Q. Yuan and S. Sclaroff, "A unified framework for gesture recognition and spatio-temporal gesture segmentation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 31, no. 9, pp. 1685-1699, September 2009.

[Aznaveh & Mirzaei+ 2008] M. M. Aznaveh, H. Mirzaei, E. Roshan and M. Saraee, "A new color based method for skin detection using RGB vector space", in *Proceedings of the Conference on Human System Interactions*, pp. 932-935, 25-27 May 2008.

[Baudel & Lafon+ 1993] T. Baudel and M. B. Lafon, "Charade: Remote Control of Objects using Free-Hand Festures", *Communications of ACM*, vol. 36, no. 7, pp. 28-35, 1993.

[Bhuyan & Ghosh+ 2005] M. K. Bhuyan, D. Ghosh, and P. K. Bora, "Designing of human computer interactive platform for robotic applications," in *TENCON IEEE Region 10*, pp.1-5, 21-24 November 2005.

[Bräunl & Feyrer+ 2001] T. Bräunl, S. Feyrer, W. Rapfand M. Reinhardt, “Parallel Image Processing”, Springer Verlag, Germany, 2001.

[Bretzner & Laptev+ 2001] L. Bretzner, I. Laptev, T. Lindeberg, S. Lenman and Y. Sundblad, "A prototype system for computer vision based human computer interaction", *Technical report ISRN KTH/NA/P-01/09-SE*, 2001.

[Brown & Thomas 2000] T. Brown and R. C. Thomas, "Finger tracking for the digital desk," *in Proceedings of First Australasian User Interface Conference*, Canberra, Australia, pp.11-16, 2000.

[Chang & Liu+ 2008] C. Chang, C. Liu and W. Tai, "Feature alignment approach for hand posture recognition based on curvature scale space", *Neurocomputing, Neurocomputing for Vision Research; Advances in Blind Signal Processing*, vol. 71, Issues 10-12, pp. 1947-1953, June 2008.

[Cho & Kim+ 1999] O. Y. Cho, H. G. Kim, S. J. Ko and S. C. Ahn, "A hand gesture recognition system for interactive virtual environment", IEEK, 36-s(4), pp. 70-82, 1999.

[Choi & Ko+ 2001] J. Choi, N. Ko and D. Ko, "Morphological gesture recognition algorithm", in *Proceedings of IEEE Region 10 International Conference on Electrical and Electronic Technology*, Coimbra, Portugal, pp.291-296, 19-22 August 2001.

[Crow 1984] F. Crow, "Summed-area tables for texture mapping". in *Proceedings of Eleventh Annual Conference on Computer Graphics and Interactive Techniques*, New York, USA, pp. 207–212, 1984.

[Crowley & Berardand+ 1995] J. L. Crowley, F. Berardand and J. Coutaz., "Finger tacking as an input device for augmented reality", in *Proceedings of International Workshop on Automatic Face and Gesture Recognition*, Zurich, Switzerland, pp. 195-200, 1995.

[Dastur & Khawaja 2010] J. Dastur and A. Khawaja, "Robotic arm actuation with 7 DOF using Haar classifier gesture recognition," in *Proceedings of the Second International Conference on Computer Engineering and Applications*, vol.1, pp. 27-29, March 2010.

[Davis & Shah 1994] J. Davis and M. Shah, "Recognizing hand gestures", in *Proceedings of European Conference on Computer Vision*, Stockholm, Sweden, pp. 331-340, 2-6 May 1994.

[Do & Jung+ 2006] J. H. Do, J. W. Jung, S. Jung, H. Jang and Z. Bien, "Advanced soft remote control system using hand gestures", *MICAI (Advances in Artificial Intelligence), LNAI*, vol. 4293, pp. 745-755, 2006.

[El-Sawah & Joslin+ 2007] A. El-Sawah, C. Joslin, N. D. Georganas and E. M. Petriu, "A framework for 3D hand tracking and gesture recognition using elements of genetic programming," in *Proceedings of the Fourth Canadian Conference on Computer and Robot Vision*, pp. 495-502, Montreal, Canada, 28-30 May 2007.

[Fels & Hinton 1993] S. S. Fels and G. E. Hinton, "Glove-Talk: A neural network interface between a data-glove and a speech synthesizer", *IEEE Transactions on Neural Networks*, vol. 4, pp. 2-8, January 1993.

[Fisher 2010] M. Fisher, "Kinect study", 2010. [Online]. Available: http://graphics.stanford.edu/˜mdfisher/Kinect.html.

[Frati & Prattichizzo 2011] V. Frati and D. Prattichizzo, "Using kinect for hand tracking and rendering in wearable haptics", in *Proceedings of the IEEE World Haptics Conference*, pp. 317-321, 21-24 June 2011.

[Freeman 1961] H. Freeman, "On the encoding of arbitrary geometric configurations", *IRE Transactions on Electronic Computers*, vol. EC -10, no. 2, pp. 260-268, July 1985.

[Freeman 1999] W. T. Freeman, “Computer vision for television and games”, in *Proceedings of International Workshop on Recognition, Analysis, and Tracking of Faces and Gestures in Real-Time Systems,* pp. 118, 1999.

[Freeman & Roth 1994] W. T. Freeman and M. Roth, "Orientation histograms for hand gesture recognition", TR-94-03a, December 1994.

[Garg & Aggarwal+ 2009] P. Garg, N. Aggarwal and S. Sofat, "Vision-based hand gesture recognition", *World Academy of Science, Engineering and Technology*, vol. 49, pp. 972-977, 2009.

[Gastaldi & Pareschi+ 2005] G. Gastaldi, A. Pareschi, S. P. Sabatini, F. Solari and G. M. Bisio, "A man-machine communication system based on the visual analysis of dynamic gestures", in *Proceedings of IEEE International Conference on Image Processing*, Genoa, Italy, vol.3, pp. III- 397-400, 11-14 September 2005.

[Graham 1991] W. Graham, "Artificial Intelligence in Engineering", John Willey & Sons, West Sussex, UK, 1991.

[Hardenberg & Berard 2001] C. V. Hardenberg and F. Berard, "Bare hand human computer interaction", in *Proceedings of the ACM workshop on Perceptive user interfaces*, Orlando, Florida, USA, pp. 1-8, 2001.

[Hoff & Lisle 2003] W. A. Hoff and J. C. Lisle, "Mobile robot control using a small display," in *Proceedings of International Conference on Intelligent Robots and Systems*, Golden, CO, USA, vol. 4, pp. 3473-3478, 27 - 31 October 2003.

[Hu & Yu+ 2000] C. Hu, Q. Yu, Y. Li and S. Ma, "Extraction of parametric human model for posture recognition using genetic algorithm", in *Proceedings of Fourth IEEE International Conference on Automatic Face and Gesture Recognition*, Grenoble, France, pp. 518-523, 28 - 30 March 2000.

[Huang & Hu+ 2010] D. Huang, W. Hu, S. Chang, "Gabor filter-based hand-pose angle estimation for hand gesture recognition under varying illumination", *Expert Systems with Applications*, vol. 38, no. 5, pp. 6031-6042, May 2011.

[Huang & Pavlovic 1995] T. S. Huang and V. I. Pavlovic, "Hand gesture modeling, analysis and synthesis", in *Proceedings of International Workshop on Automatic Face and Gesture Recognition*, Zurich, pp.73-79, 1995.

[Just & Marcel 2009] A. Just and S. Marcel, "A comparative study of two state-of-the-art sequence processing techniques for hand gesture recognition", *Computer Vision and Image Understanding*, vol. 113, no. 4, pp. 532-543, April 2009.

[Keaton & Dominguez+ 2002] T. Keaton, S. M. Dominguez and A. H. Sayed, "SNAP & TELL: a multimodal wearable computer interface for browsing the environment", in *Proceedings of Sixth International Symposium on Wearable Computers*, Seattle, WA, USA, pp.75–82, 2002.

[Kendon 2004] A. Kendon, "Gesture: visible action as utterance", Cambridge University Press. UK, 2004.

[Keskin & Aran+ 2005] C. Keskin, O. Aran and L. Akarun, "Real time gestural interface for generic applications", in *Proceedings of European Signal Processing Conference*, Antalya, Turkey, 2005.

[Kim & Fellner 2004] H. Kim and D. W. Fellner, "Interaction with hand gesture for a back-projection wall", in *Proceedings of Computer Graphics International*, pp. 395-402, 19 June 2004.

[Kim & Lee 2008] J. M. Kim and W. K. Lee, "Hand shape recognition using fingertips", in *Proceedings of Fifth International Conference on Fuzzy Systems and Knowledge Discovery*, Jinan, Shandong, China, pp.44-48, 2008.

[Kohler 1996] M. Kohler, "Vision based remote control in intelligent home environments", *3D Image Analysis and Synthesis*, pp. 147-154, 1996.

[Kroeker 2010] K. L. Kroeker, "Alternate interface technologies emerge", *Communications of the ACM*, vol. 53, no. 2, pp. 13-15 February 2010.

[Kuno & Sakamoto+ 1994] Y. Kuno, M. Sakamoto, K. Sakata and Y. Shirai, "Vision-based human computer interface with user centered frame", in *Proceedings of Intelligent Robots and Systems*, pp.2023-2029, 12-16 September 1994.

[Lee & Chun 2009] B. Lee and J. Chun, "Manipulation of virtual objects in marker-less AR system by fingertip tracking and hand gesture recognition", in *Proceedings of the Second International Conference on Interaction Science: Information Technology, Culture and Human*, Seoul, Korea, pp. 1110-1115, 2009.

[Lee & Kim 1999] H.-K. Lee and J H. Kim, "HMM based threshold model approach for gesture recognition", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, no. 10, pp. 961-973, October 1999.

[Lee & Lee+ 2004] J. Lee, Y. Lee, E. Lee and S. Hong, "Hand region extraction and gesture recognition from video stream with complex background through entropy analysis", in *Proceedings of the Twenty Sixth Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, San Francisco, CA, USA, pp. 1513-1516, 1-5 September 2004.

[Lee & Park 2009] D. Lee and Y. Park, "Vision-based remote control system by motion detection and open finger counting", *IEEE Transactions on Consumer Electronics*, vol. 55, no. 4, pp. 2308-2313, November 2009.

[Li & Greenspan 2011] H. Li and M. Greenspan, "Model-based segmentation and Recognition of Dynamic Gestures in Continuous Video Streams", *Pattern Recognition*, August 2011.

[Li & Wachsmuth+ 2007] Z. Li, S. Wachsmuth, J. Fritsch and G. Sagerer, "View-adaptive manipulative action recognition for robot companions," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp.1028-1033, 29 October 2007.

[Liang & Ouhyoung 1998] R. Liang and M. Ouhyoung, "A real-time gesture recognition system for sign language", in *Proceedings of Third International Conference on Automatic Face Gesture Recognition*, pp. 558–567, 14-16 April 1998.

[Lien & Huang 1998] C. C. Lien and C. Huang, "Model-based articulated hand motion tracking for gesture recognition", *Image and Vision Computing*, vol. 16, no. 2, pp. 121-134, 20 February 1998.

[Locken & Fitzgibbon 2002] R. Locken and A. W. Fitzgibbon. "Real gesture recognition using deterministic boosting", in *Proceedings of the British Machine Vision Conference*, 2002.

[Lu & Shark+ 2009] G. Lu, L.-K. Shark, G. Hall and U. Zeshan, "Dynamic hand gesture tracking and recognition for real time immersive virtual object manipulation", in *Proceedings of the International Conference on Cyber Worlds*, pp. 29-35, 7-11 September 2009.

[Mahmoudi & Parviz 2006] F. Mahmoudi and M. Parviz, "Visual hand tracking algorithms", *Geometric Modeling and Imaging- New Trends*, pp. 228-232, 16-18 August 2006.

[Malassiotis & Strintzis 2008] S. Malassiotis and M. G. Strintzis, "Real-time hand posture recognition using range data", *Image and Vision Computing*, vol. 26, no. 7, pp. 1027-1037, 2 July 2008.

[Man & Qiu+ 2005] W. T. Man, S. M. Qiu and W. K. Hong, "ThumbStick: a novel virtual hand gesture interface," *IEEE International Workshop on Robot and Human Interactive Communication*, pp. 300- 305, August 2005.

[Maung 2009] T. H. H. Maung, "Real time hand tracking and gesture recognition System using Neural Networks", *World Academy of Science, Engineering and Technology*, vol. 50, Issue. February, pp. 466-470, 2009.

[McConnell 1986] R. K. McConnell, "Method of and apparatus for pattern recognition", U. S. Patent No. 4567610, January 1986.

[Messery 1998] T. Messery, Static hand gesture recognition Report.

[Mitra & Acharya 2007] S. Mitra and T. Acharya, "Gesture recognition: A survey", *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Review*, vol. 37, no 3, pp. 2127-2130, May 2007.

[Mohammad & Nishida+ 2009] Y. Mohammad, T. Nishida and S. Okada, "Unsupervised simultaneous learning of gestures, actions and their associations for Human-Robot Interaction," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 2537-2544, 10-15 October 2009.

[Morimoto & Miyajima+ 2007] K. Morimoto, C. Miyajima, N. Kitaoka, K. Itou, and K. Takeda, "Statistical segmentation and recognition of fingertip trajectories for a gesture interface", in *Proceedings of the Ninth International Conference on Multimodal Interfaces*, Nagoya, Aichi, Japan, pp. 54-57, 12-15 November 2007.

[Ng & Ranganath 2002] C. W. Ng and S. Ranganath, "Real-time gesture recognition system and application", *Image and Vision Computing*, vol. 20, Issues 13-14, pp. 993-1007, December 2002.

[Nguyen & Pham+ 2009] D. D. Nguyen, T. C. Pham and J. W. Jeon, "Fingertip detection with morphology and geometric calculation", in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, St. Louis, USA, pp. 1460-1465, October 11-15, 2009.

[Nolker & Ritter 2000] C. Nolker and H. Ritter, "Parameterized SOMs for hand posture reconstruction", in *Proceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks*, Portland, USA, vol. 4, pp. 139-144, November 2000.

[Nolker & Ritter 2002] C. Nolker and H. Ritter, "Visual recognition of continuous hand postures", *IEEE Transactions on neural networks*, vol. 13, no. 4, pp. 983-994, July 2002.

[Oka & Sato+ 2002a] K. Oka, Y. Sato and H. Koike, "Real time tracking of multiple fingertips and gesture recognition for augmented desk interface systems", in *Proceedings of the Fifth IEEE International Conference on Automatic Face and Gesture Recognition*, Washington, D.C., USA, pp. 411–416, May 2002.

[Oka & Sato+ 2002b] K. Oka, Y. Sato and H. Koike, "Real time fingertip tracking and gesture recognition", *IEEE Computer Graphics and Applications*, vol. 22, no. 6, pp. 64–71, December 2002.

[Ong & Ranganath 2005] S. C. W. Ong and S. Ranganath, "Automatic sign language analysis: A Survey and the future beyond lexical meaning", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.27, no. 6, June 2005.

[Ozer & Lu+ 2005] I. B. Ozer, T. Lu and W. Wolf, "Design of a real time gesture recognition system : High Performance through algorithms and software", *IEEE Signal Processing Magazine,* pp 57-64, May 2005.

[Pavlovic & Sharma+ 1997] V. I. Pavlovic, R. Sharma and T. S. Huang, "Visual interpretation of hand gestures for human-computer interaction: A review", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, pp. 677-695, July 1997.

[Pickering 2005] C. A. Pickering, "The search for a safer driver interface: A review of gesture recognition human machine interface", *IEE Computing and Control Engineering*, pp. 34-40, 2005.

[Premaratne & Nguyen 2007] P. Premaratne and Q. Nguyen, "Consumer electronics control system based on hand gesture moment invariants", *IET Computer Vision*, vol. 1, no. 1, pp. 35-41, March 2007.

[Quek 1994] F. K. H. Quek, "Toward a vision-based hand gesture interface", in *Proceedings of the Virtual Reality System Technology Conference*, pp.17-29, 1994.

[Quek & Mysliwiec+ 1995] F. K. H. Quek, T. Mysliwiec and M. Zhao, "Finger mouse: A free hand pointing computer interface", in *Proceedings of International Workshop on Automatic Face and Gesture Recognition*, Zurich, Switzerland, pp. 372-377, 1995.

[Raheja & Jain+ 2010] J.L. Raheja, R. Jain, P. Mohapatra, "Visual Approach to Dynamic Hand Gesture Recognition for Human Compuer Interface", *International Journal of Recent Trends in Engineering and Technology*, vol. 3, no. 3, pp. 190-194.

[Raheja & Shyam+ 2010] J. L. Raheja, R. Shyam, U. Kumar and P. B. Prasad, "Real-time robotic hand control using hand gesture", in *Proceedings of the Second International Conference on Machine Learning and Computing*, Bangalore, India, pp. 12-16, 9-11 February 2010.

[Rashid & Al-Hamadi+ 2009] O. Rashid, A. Al-Hamadi and B. Michaelis, "A Framework for the Integration of Gesture and Posture Recognition using HMM and SVM", in *IEEE International Conference on Intelligent Computing and Intelligent Systems*, Shanghai, pp. 572-577, 20-22 November 2009.

[Sanghi & Arora+ 2008] A. Sanghi, H. Arora, K. Gupta and V. B. Vats, "A fingertip detection and tracking system as a virtual mouse, a signature input device and an application selector", in *Proceedings of the Seventh International Caribbean Conference on Devices, Circuits and Systems*, Cancum, Mexico, pp. 1-4, 28-30 April 2008.

[Sato & Kobayashi+ 2000] Y. Sato, Y. Kobayashi and H. Koike, "Fast tracking of hands and fingertips in infrared images for augmented desk interface", in *Proceedings of Fourth IEEE International Conference on Automatic Face and Gesture Recognition*, Grenoble, France, 2000, pp. 462–467.

[Schlomer & Poppinga+ 2008] T. Schlomer, B. Poppinga, N. Henze and S. Boll, "Gesture recognition with a Wii Controller", in *Proceedings of the Second International Conference and Embedded Interaction*, Bonn, Germany, pp. 11-14, 18-20 February 2008.

[Shimada 1998] N. Shimada et al., "Hand gesture estimation and model refinement using monocular camera—Ambiguity limitation by inequality constraints," in *Proceedings of IEEE Third Conference on Face and Gesture Recognition*, pp. 268-273, 14-16 April 1998.

[Shimizu & Yoshizuka+ 2006] M. Shimizu, T. Yoshizuka and H. Miyamoto, "A gesture recognition system using stereo vision and arm model fitting", in *Proceedings of Third International Conference on Brain-Inspired Information Technology*, Kitakyushu, Japan, pp 89–92, 27-29 September 2006.

[Shin & Lee+ 2006] J.H. Shin, J.S. Lee, S.-K. Kil, D.F. Shen, J.G. Ryu, E.H. Lee, H.K. Min and S.H. Hong, "Hand region extraction and gesture recognition using entropy analysis", *International Journal of Computer Science and Network Security*, vol. 6, Issue 2A, February 2006.

[Shin & Tsap+ 2004] M. C. Shin, L. V. Tsap and D. B. Goldgof, "Gesture recognition using Bezier curves for visualization navigation from registered 3-D data", *Pattern Recognition*, vol. 37, no. 5, pp. 1011–1024, May 2004.

[Sivanandam & Deepa 2007] S. N. Sivanandam and S. N. Deepa, "Principles of soft computing", Wiley India Edition, New Delhi, 2007.

[Sonka & Hlavac+ 1999] M. Sonka, V. Hlavac and R. Boyle, "Image processing, analysis, and machine vision", Brooks/Cole Publishing Company, 1999.

[Starner & Pentland 1995] T. Starner and A. Pentland, "Real-time American sign language recognition from video using hidden Markov models," in *Proceedings of International Symposium on Computer Vision*, pp. 265–270, 21-23 November 1995.

[Stefan & Athitsos+ 2008] A. Stefan, V. Athitsos, J. Alon and S. Sclaroff, "Translation and scale invariant gesture recognition in complex scenes", in *Proceedings of Firth International Conference on Pervasive Technologies Related to Assistive Environments*, Greece, July 2008.

[Stergiopoulou & Papamarkos 2009] E. Stergiopoulou and N. Papamarkos, "Hand gesture recognition using a neural network shape fitting technique", *Engineering Applications of Artificial Intelligence*, vol. 22, no. 8, pp. 1141-1158, December 2009.

[Sturman & Zeltzer 1994] D. Sturman and D. Zeltzer, "A survey of glove-based input", *IEEE Transactions on Computer Graphics and Applications*, vol. 14, no. 1, pp. 30-39, January 1994.

[Suk & Sin+ 2010] H. Suk, B. Sin and S. Lee, "Hand gesture recognition based on dynamic Bayesian network framework", *Pattern Recognition*, vol. 43, no. 9, pp 3059-3072, September 2010.

[Tarrataca & Santos+ 2009] L. Tarrataca, A. C. Santos and J. M. P. Cardoso, "The current feasibility of gesture recognition for a smartphone using J2ME", in *Proceedings of the ACM Symposium on Applied Computing*, pp. 1642-1649, 2009.

[TET 2011] The Teardown, Engineering & Technology, vol. 6, no. 3, pp. 94-95, April, 2011.

[Therrien 1989] C. W. Therrien, "Decision estimation and classification: an introduction to pattern recognition and related topics", Wiley & Sons, Inc 1989.

[Tomita & Ishii 1994] A. Tomita and R. J. Ishii, "Hand shape extraction from a sequence of digitized gray-scale images", in *Proceedings of Twentieth International Conference on Industrial Electronics, Control and Instrumentation*, Bologna, Italy, vol. 3, pp. 1925–1930, 5-9 September 1994.

[Triesch & Malsburg 1997] J. Triesch and C. V. D. Malsburg, "Mechanical gesture recognition", in *Gesture Workshop*, pp. 233-244, 1997.

[Trivino & Bailador 2007] G. Trivino and G. Bailador, "Linguistic description of human body posture using fuzzy logic and several levels of abstraction", in *Proceedings of the IEEE Conference on Computational Intelligence for Measurement Systems and Applications*, Ostuni, Italy, pp. 105-109, 27-29 June 2007.

[Tsalakanidou & Forster+ 2005] F. Tsalakanidou, F. Forster, S. Malassiotis and M. G. Strintzis, "Real-time acquisition of depth and color images using structured light and its application to 3D face recognition", *Real-Time Imaging, Special Issue on Multi-Dimensional Image Processing*, vol. 11, Issue 5-6, October – December 2005.

[Verma & Dev 2009] R. Verma and A. Dev, "Vision-based hand gesture recognition using finite state machines and fuzzy logic", in *Proceedings of the International Conference on Ultra-Modern Telecommunications & Workshops*, pp. 1-6, 12-14 October 2009.

[Villani & Heisler+ 2007] N. A. Villani, J. Heisler and L. Arns, "Two gesture recognition systems for immersive math education of the deaf", in *Proceedings of the First International Conference on Immersive Telecommunications*, Bussolengo, Verona, Italy, October 2007.

[Wang & Cannon 1993] C. Wang and D. J. Cannon, "A virtual end-effector pointing system in point-and-direct robotics for inspection of surface flaws using a neural network-based skeleton transform", in *Proceedings of IEEE International Conference on Robotics and Automation*, vol. 3, pp. 784-789, 2-6 May, 1993.

[Wang & Mori 2009] Y. Wang and G. Mori, "Max-margin hidden conditional random fields for human action recognition", in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, Miami, Florida, USA, pp. 872-879, 20-25 June, 2009.

[Werbos 1994] P. J. Werbos, "The roots of backpropagation: from ordered derivatives to neural networks and political forecasting", New York, NY: John Wiley & Sons, Inc., 1994.

[WIKIa] Wikipedia.org, [Online]. Available: http://en.wikipedia.org/wiki/Cluster_analysis#Fuzzy_c-means_clustering.

[WIKIb] Wikipedia.org, [Online]. Available:

http://en.wikipedia.org/wiki/Kinect

[WIKIc] Wikipedia.org, [Online]. Available: http://en.wikipedia.org/wiki/Summed_area_table

[Wilamowski & Chen 1999] B. Wilamowski and Y. Chen, "Efficient algorithm for training neural networks with one hidden layer", in *Proceedings of International Joint Conference on Neural Network*, vol. 3, pp. 1725-1728, 1999.

[Wu & Shan+ 2000] Y. Wu, Y. Shan, Z. Zhangy and S. Shafer, "VISUAL PANEL: from an ordinary paper to a wireless and mobile input device", Technical Report, MSRTR 2000, Microsoft Research Corporation, 2000.

[Xu & Zhu 2009] Z. Xu and H. Zhu, "Vision-based detection of dynamic gesture", in *Proceedings of the International Conference on Test and Measurement*, pp.223-226, 5-6 December 2009.

[Yang & Jin+ 2005] D. Yang, L. W. Jin, J. Yin and others, "An effective robust fingertip detection method for finger writing character recognition system", in *Proceedings of the Fourth International Conference On Machine Learning And Cybernetics*, Guangzhou, China, pp. 4191–4196, 2005.

[Ying & Song+ 2008] H. Ying, J. Song, X. Renand and W. Wang, "Fingertip detection and tracking using 2D and 3D information", in *Proceedings of the Seventh World Congress on Intelligent Control and Automation*, Chongqing, China, pp. 1149-1152, 25-27 June 2008.

[Yoon & Soh+ 2001] H.-S. Yoon, J. Soh, Y. J. Bae and H. S. Yang, "Hand Gesture recognition using combined features of location, angle and velocity", *Pattern Recognition*, vol. 34, no. 37, pp. 1491-1501, 2001.

[Zadeh 1965] L.A. Zadeh, "Fuzzy Sets", *Information and Control*, vol. 8, pp. 338-353, 1965.

[Zaki & Shaheen 2011] M. M. Zaki and S. I. Shaheen, "Sign language recognition using a combination of new vision based features", *Pattern Recognition Letters*, vol. 32, no. 4, pp. 572-577, 1 March 2011.

[Zhang & Lin+ 2009] J. Zhang, H. Lin and M. Zhao, "A fast algorithm for hand gesture recognition using relief", in *Proceedings of Sixth International Conference on Fuzzy Systems and Knowledge Discovery*, Tinajin, China, pp. 8-12, 14-16 August 2009.

[Zhou & Ruan 2006] H. Zhou and Q. Ruan, "A real-time gesture recognition algorithm on video surveillance", in *Proceedings of Eighth International Conference on Signal Processing*, Beijing , China, pp. 1754-1757, November 2006.

[Zou & Xiao+ 2009] S. Zou, H. Xiao, H. Wan and X. Zhou, "Vision-based hand interaction and its application in pervasive games", in *Proceedings of the 8th International Conference on Virtual Reality Continuum and its Applications in Industry*, Yokohama, Japan, pp. 157-162, 2009.

Publications

Book Chapters

1. A. Chaudhary, J.L. Raheja, K. Das, S. Raheja, “A Survey on Hand Gesture Recognition in context of Soft Computing”, *Published as Book Chapter in Advanced Computing,* CCIS, Springer Berlin Heidelberg, Part III, vol. 133, pp. 46-55, 2010.

2. A. Chaudhary, J.L. Raheja, K. Singal, S. Raheja, “An ANN based Approach to Calculate Robotic fingers positions”, *Published as Book Chapter in Advances in Computing and Communications,* CCIS, Springer Berlin Heidelberg, vol. 192, pp. 488-496, 2011.

Peer Reviewed Conferences

3. A. Chaudhary, J.L. Raheja, "ABHIVYAKTI: A Vision Based Intelligent System for Elder and Sick Persons”, in *Proceedings of 3rd IEEE International Conference on Machine Vision,* Hong Kong, pp. 361-364, 28-30 December 2010.

4. J.L. Raheja, K. Das, A. Chaudhary, “An Efficient Real Time Method of Fingertip Detection”, in *Proceedings of 7th International Conference on Trends in Industrial Measurements and Automation,* CSIR Complex, Chennai, India, pp. 447-450, 6-8 January 2011.

5. A. Chaudhary, J.L. Raheja, K. Das, “A Vision based Real Time System to Approximate Fingers Angles”, in *Proceedings of IEEE International Conference on Computer Control and Automation,* Jeju Island, South Korea, pp. 118-122, 1-3 May 2011.

6. J.L. Raheja, A. Chaudhary, K. Singal, "Tracking of Fingertips and Centre of Palm using KINECT", in *Proceedings of 3rd IEEE International Conference on Computational Intelligence, Modelling and Simulation,* Langkawi, Malaysia, pp. 248-252, 20-22 September 2011.

7. J.L. Raheja, M.B.L. Manasa, A. Chaudhary, S. Raheja, "ABHIVYAKTI: Hand Gesture Recognition using Orientation Histogram in different light conditions", in *Proceedings of the 5th Indian International Conference on Artificial Intelligence*, Tumkur, India, pp. 1687-1698, 14-16 December 2011.

Posters

8. A. Chaudhary, M.B.L. Manasa, J.L. Raheja, "Light invariant Neuro-Vision System for Elder/Sick people to express their needs into Lingual Description", *Microsoft Research India's annual research symposium TechVista 2012,* Kolkata, India, 20 January 2012.

Journals

9. A. Chaudhary, J.L. Raheja, K. Das, S. Raheja, "Intelligent Approaches to interact with Machines using Hand Gesture Recognition in Natural way: A Survey", *International Journal of Computer science and engineering Survey,* vol. 2, issue 1, pp. 111-122, 2011.

10. J.L. Raheja, K. Das, A. Chaudhary, "Fingertip Detection: A Fast Method with Natural Hand", *International Journal of Embedded Systems and Computer Engineering,* vol. 3, no. 2, pp.85-89, December 2011. (indexed Scopus & EI)

11. A. Chaudhary, J. L. Raheja, S. Raheja "A Vision based Geometrical Method to find Fingers Positions in Real Time Hand Gesture Recognition", *Journal of Software,* Academy Publisher, Finland, vol. 7, no. 4 , pp. 861-869, April 2012.

12. A. Chaudhary, K. Vatwani1, T. Agrawal, J.L. Raheja, "A Vision based Method to find Fingertips in Closed Hand", *Journal of Information Processing Systems*, Vol. 8, No. 3, Sep 2012, pp. (in press)

13. A. Chaudhary, J. L. Raheja, K. Das, S. Raheja, “Both Hands’ Fingers’ Angle Calculation from Live Video”, *International Journal of Computer Vision and Image Processing*, IGI Global, USA, vol. 2, issue 2, pp. , 2012.(in press)

14. A. Chaudhary, J. L. Raheja, “Bent Fingers’ Angle Calculation using Supervised ANN to Control Electro-Mechanical Robotic Hand”, *Computers & Electrical Engineering*, Elsevier, vol. , no., pp. , 2012. (IF 2012: 0.484) (in press)

15. A. Chaudhary, M.B.L. Manasa, J.L. Raheja, “Light invariant Gesture Recognition”, *Neurocomputing*, Elsevier, vol., issue, pp., 2013.(communicated)

Vitas

BRIEF BIO OF CANDIDATE

Ankit Chaudhary received his Master of Engineering from Dept. of Computer Science, Birla Institute of Technology & Science, Pilani, India and currently pursuing Ph.D. in Computer Vision from Machine Vision Lab, CEERI Pilani and Dept. of Computer Science, BITS Pilani, India. His areas of research interest are Computer Vision, Artificial Intelligence and Embedded Systems. He has also worked at BHARTI Telesoft, CITRIX R&D and AVAYA INC as software programmer.

BRIEF BIO OF SUPERVISOR

Dr. Jagdish Lal Raheja received his M. Tech from Dept. of Electronics Engineering, Indian Institute of Technology, Kharagpur, India in 1986 and Ph.D. from Technical University of Munich, Germany in 2005. He joined Central Electronics Engineering Research Institute (CEERI/CSIR), Pilani, India in 1990 and currently he is Head of Machine Vision lab at Digital Systems Group, CEERI, Pilani, INDIA. His areas of research interest are Image Processing, Embedded Systems and Human Computer Interface and Perception Engineering.

He has more than 22 year experience in research and supervised more than 100 master thesis. He has been involved in many govt. and international projects and got 5 patents and 2 copyrights. He has published more than 80 papers in referred journals & international conference of repute and authored two books. He has been DAAD and IFTA fellow.