Learning based Hand Gesture Recognition from RGBD sensors

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by

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to the

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Certificate

This is to certify that dissertation entitled **"Learning based Hand Gesture Recognition from RGBD sensors"** is being submitted by **Bindu Verma** (Enrollment Number 13/10/MT/005) to the **School of Computer & Systems Sciences, Jawaharlal Nehru University, New Delhi-110067, India**, in partial fulfilment of the requirements for award of the degree of **"Master of Technology"** in **"Computer Science & Technology"**. This work is carried out by herself in the School of Computer & Systems Sciences under the supervision of **Dr. Ayesha Choudhary**. The matter personified in the dissertation has not been submitted for the award of any other degree or diploma.

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Declaration

I hereby declare that the dissertation work entitled **"Learning based Hand Gesture Recognition from RGBD sensors"** in partial fulfilment of the requirements for the award of degree of **"Master of Technology"** in **"Computer Science & Technology"** and submitted to the **School of Computer & Systems Sciences, Jawaharlal Nehru University, New Delhi-110067, India**, is the authentic record of my own work carried out during the time of Master of Technology under the supervision of **Dr. Ayesha Choudhary**. This dissertation comprises only my own work. Wherever contribution of others are involved, every effort is made to indicate this clearly with due reference to the literature, and acknowledgement of collaborative research and discussions. The matter personified in the dissertation has not been submitted for the award of any other degree or diploma.

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"Dedicated to my family...."

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(Bindu Verma)

Abstract

In our hand gesture recognition system we propose an unsupervised learning based hand gesture recognition framework. We use the RGBD sensor from Microsoft called kinect to gather depth data along with RGB data. We use this depth data for detecting the hand in the image. We then, apply our incremental clustering algorithm for finding the shape of the hand in terms of the number of open fingers & the labels on these fingers. The recognition is carried out based on various parameters such as number of open fingers, their orientation and distances. Experimental result shows that our system is correctly able to recognize these gestures and is robust.

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Chapter 1

Introduction

Hand gesture is a non-verbal cue which provides an interface for communication between persons as well as man and machine. Each hand gesture is defined by specific palm finger position and their shape. Automated recognition of these hand gestures will help in developing a system that makes man machine communication easy. When our hand is used as an input device there is no need of any other communication medium. The main aim of automated hand gesture recognition is to develop a set of techniques that automatically recognize hand gestures from images and videos and classifies these hand gestures with high degree of accuracy.
The understanding of how hand moves in space and recognizing a particular motion as hand gesture is challenging. Vision based hand gesture recognition provides a framework to user for communication with computer in a natural way. Human computer interaction is an active research area in the field of computer vision and pattern recognition.
In general hand gestures provide a natural mode of communication with machines therefore a human computer interface using hand gesture can replaces mouse and keyboards. Hand gesture based communication removes physical contact with machine and enable communication at a distance. Hand gesture recognition (HGR) is an important area of research because it has a lot of application in areas such as sign language recognition, assistive living, medical, games etc.

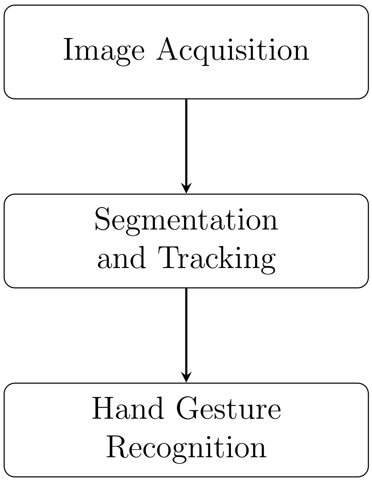


Figure 1.1: Hand Gesture Recognition System

There are two types of hand gestures:

- Static hand gesture
- Dynamic hand gesture

Static hand gesture refers to the static shape of the palms and fingers that expresses some meaning for communication.

Dynamic hand gesture is composed of a series of hand movements. Dynamic hand gesture provides a richer communication with the help of motion information.

In general, there are three main phases in hand gesture recognition systems:

- Collection of relevant hand gesture data.
- Segmentation and tracking of hand gesture.
- Gesture recognition and classification.

Figure 1.1 shows the flowchart of the hand gesture recognition systems. There are two main challenges in hand gesture recognition is (i) identification of which body part is involved in gesture (ii) recognition of hand gesture. Hand is a very small part of the body therefore hand detection is challenging because of the small size of the hand.

Different types of sensors such as data gloves, optical sensor, kinect sensor, camera are used to capturing hand gestures. Hand gesture captured by optical sensor have a poor lighting condition and cluttered background. Thus optical sensor fails to recognize hand gesture successfully. For more robust hand gesture recognition data gloves are used. Data gloves is an electronic device and user require to wear it on his hand. Data gloves hides the naturalness of hand gesture recognition system and also these gloves are very expensive. Accuracy of recognition is depends upon the condition under which data is being taken such as poor lighting condition, cluttered background and color of the background. Microsoft introduced a new device kinect sensor. Kinect sensor captures the RGB image and corresponding depth map. Depth map contain information about distance of the object from the viewpoint. Front most object from the viewpoint have a lower distance. Depth map also gives information about third dimension.

Various techniques are used for hand detection and feature extraction such as skin model[12], [13], [14], [18], contour detection[31], [36], skeleton detection [3], depth data and thresholding decomposition[4], [5], [6], [7], [8] and Karhunen-Loeve Decomposition [44], feature vector[15], [17], hierarchical clustering[45].

Hidden markov model[15], [16], [17], [18], [19], support vector machine and PCA [34], [35], [36], [37], artificial neural network [22], [23], [24], [25], finite state machine[29], [30], [31], [32], K-NN classifiers[13], [35], Bayesian Network [40], [41] and many more techniques are used in literature for hand gesture recognition.

In chgapter 2, we give a detailed survey of the state of the art.

1.1 Proposed Approach

There are a number of challenges in hand gesture recognition:

- Detection of hand from image is difficult because hand is a very small object as compared to the full body.
- Accuracy and usefulness of automated hand gesture recognition system.

- The amount of background noise because of cluttered background, poor lighting condition also cause tracking and recognition difficulties.
- Recognition accuracy of system depends upon the type of camera, configuration of camera and distance from camera.
- Limited number of equipment used and image noise also cause variation in recognition.

Our Complete hand gesture recognition system is divided into seven different module. These steps are shown in below:

- Data Collection
- Hand Detection using Depth Data
- Preprocessing
- Clustering of Hand Finger and Palm
- Feature Collection
- Labellings of the Detected clusters
- Hand Gesture Recognition module

In our proposed work we supposed to use kinect sensor device for data collection. We have given a real time implementation of hand gesture recognition systems that makes man machine communication easy.

1.2 Organization of thesis

This thesis contains five chapters in which we describes the problem of automated hand gesture recognition system.

Chapter 1 is the introductory chapter of hand gesture recognition system. This chapter gives the brief overview of thesis.

In Chapter 2 we discussed the state of the art in hand gesture recognition. We have done a survey on various techniques used in hand gesture recognition.

Chapter 3 contains proposed approach. In this chapter we have given our proposed model and algorithm. A complete structure of our hand gesture recognitions framework are explained.

Chapter 4, contains the experimental results and discussion have been carried out in order to analyze the effectiveness of the proposed model.

Finally we conclude in Chapter 5 and also discuss the future work we plan to continue in this area.

Chapter 2

Literature Survey

In the literature, there are number of techniques proposed for hand gesture recognition. In general, there are two steps for hand gesture recognition system (i) location of the hand involved in the gesture (ii) gesture classification. The process of hand tracking and gesture recognition can be categorized into two categories: (i) data gloves based (ii) computer vision based methods. Data gloves is a electronic device having a sensor attach to it and transmit electrical signals for the movement of the hand. The Microsoft Kinect sensor is used to captured the RGB image and corresponding depth map.

2.1 Kinect based hand gesture recognition

Kinect sensor based gesture recognition techniques are becoming popular since the depth data associated with the RGB images are readily available when using Kinect. Here, we discuss a few of the techniques present in the literature using Kinect.

2.1.1 Part based hand gesture recognition

In part based gesture recognition, the authors focus mainly on fingers rather than complete hand for hand gesture recognition. The authors [2] use Kinect sensor device to capture the RGB images of the hand gesture and corresponding depth map. Then, they use a thresholding function on the depth map to segment the hand shape. In thids work, there are two major modules (i) hand detection (ii) gesture recognition. The authors use a hand tracking function to locate the hand then after thresholding certain depth interval they obtain a rough hand region. They represent the detected hand on a time series curve. This time series curve represents the fingers very clearly. Hand gesture recognition is carried out using template matching in which Finger-Earth Mover's Distance (FEMD) between the template and the input hand is calculated. For finger detection from time series curve, the authors have used Thresholding Decomposition and Near Convex Decomposition.

2.1.2 Super-pixel Based Hand Gesture Recognition

Chong Wang, et al. in [3], used Kinect to collect the data of input hand gesture and corresponding depth map. Using depth and skeleton information hands are extracted. The depth information and hand texture form a super-pixel which contains the overall shape and information of hand gesture. Then super-pixel earth mover's distance are calculated to find the dissimilarities between hand gesture, to classify and recognize hand gestures.

2.1.3 Depth based hand gesture recognition

Dominio, et al. [4] used simple depth camera to capture the depth data of hand gesture. Hands are extracted from the depth data and divided into two parts: palm and fingers. Then different features like fingertips distance, hand center, structure of hand contour and so on. Finally, a multi class support vector machine (SVM) classifier is used to recognize the hand gesture.

Kapuscinski, Tomasz, et al. [5] proposed hand gesture recognition based on 3D information. A descriptor is prepared with the help of viewpoint feature histogram. To make the recognition more accurate scene is divided into small number of 3D cells. Then, viewpoint feature histogram (VFH) is calculated. Two classifiers are used (i) Nearest neighbor with dynamic time wrapping (ii) hidden Markov model (HMM).

Hand gestures are recognized using nearest neighbor classifiers.

Chen, Zhi-hua, et al. [6] proposed a framework for HGR system in real time. Hand region are extracted using some background extraction techniques. Then, fingers and palm are divided for finger recognition and labeling is applied to detect the fingers and recognize the hand gesture.

Xie, Renqiang, et al. [7] perform hand gesture recognition using a wearable accelerometer based smart ring. The accelerometer based wearable ring captures the patterns of motion of hand. Hand gestures are divided into two type: simple hand gestures and complex hand gestures. Complex hand gestures are a sequence of simple hand gestures. Hand gestures are extracted by applying a simple hand segmentation algorithm. The detected hand gesture is then encoded and similarity between input gesture and template gestures are determined.

Wu, Chih-Hung, et al. [8] author proposed dynamic hand gesture recognition using depth information. In the preprocessing steps background subtraction techniques used to extract out the important regions. Once the hands are extracted, the hand features are extracted and these features are used for classification and recognition of hand gestures using support vector machine (SVM) based classification.

In [9] the authora used three different method for feature extraction based on Radon transformation. Depth map images are used as the input gesture. By averaging values, Radon & R transform reduces the features of Radon transform. Discrete cosine transform recalculates the images from spatial into frequency domain. The energy of the graph from Radon transform are obtained and R transform creates ID-shape curves in different direction. SVM is then used for classification of feature vectors.

2.2 Exemplar based approach for dynamic hand gesture recognition

For dynamic hand gesture recognition Xiaohui Shen, et al. [10] proposed an exemplar-based approach from motion divergence field. They calculate the optical flow. Then, divergence fields are derived and normalized to gray images, which converts the gestural motion pattern into spatial image pattern. From the divergence field, important regions are extracted by using maximally stable extremal region (MSER) feature detection method. From every detected region to characterize the local motion pattern a descriptor is extracted. Pre-trained hierarchical vocabulary trees are used to index the gesture sequence with their descriptors. Then, the test gesture is recognized using the term frequency-inverse document frequency scheme (TF-IDF) to match with the database.

2.3 Hidden Markov Model based gesture recognition

Hidden Markov Models (HMMs) have been used for classifying hand gestures also since the hand gestures contain a temporal as well as spatial information. This information is stored in a one dimensional feature vector and used as an input in Hidden Markov Model (HMM) such as in H. Lee and J. Kim [11] for hand gesture recognition. In [12], also the authors use hidden Markov model for hand gesture classification. To locate the moving hand they apply a real time hand tracking algorithm and the apply an algorithm like thresholding, skin color detection, edge detection to extract the desired hand gesture. Then, the authors use Fourier Descriptor (FD) and motion analysis to calculate the feature vector which contains the temporal as well as spatial information. These feature vectors are used in HMM for gesture classification.

Yoon, Ho-Sub, et al. [13] use hidden Markov model with combined feature velocity, angle and location. On the basis of skin color and hand motion, the hand positions are located. Then, by using a hand tracking algorithm, the centroid of the hand is found that gives hand trajectory. A feature vector is prepared with the help of location, angle and velocity. K-mean clustering along with HMM use for hand gesture classification.

Elmezain, Mahmoud, et al. [14] use Hidden Markov Model for hand gesture recognition. They also use skin color segmentation and hand tracking. Then, for feature extraction vector quantization and gesture path to find the feature vector. Then, HMM is used for gesture classification. Liu, Nianjun in [15] and Min, Byung-Woo et al. in [16] also used HMM for hand gesture recognition. Lian, Kuang-Yow et al. in [17] use inertial measurement unit (IMU) to detect the hand movement. This sensor gives variation in the gesture data. Hierarchical hidden Markov models are also used to recognize the gestures corresponding to the 10 Arabic numbers.

Irteza et al. in [18] proposed a hand gesture recognition using hidden Markov model (HMM) in 3D environment. Author used skin color model to detect the hand from input hand gesture sequences and then this data is processed to extract the feature vector. In feature extraction, three features are extracted i e. angle, velocity and location of the gesture. They then use hidden Markov model for dynamic hand gesture recognition. Liu, Kui, et al. [19] use Kinect depth camera and wireless inertial body sensor to collect the data. Signal from depth camera are used as an input to the HMM classifier. The authors use multiple HMMs and the outcome of multiple HMMs are combined and produce a mixture model having high recognition accuracy. In [20], the author proposed a recognition of hand gesture before it completed. Hidden semi Markov model (HSMM) have also been used for gesture recognition. In both partial gesture as well as in and complete gesture recognition, the trajectory information is used as an input in semi hidden Markov model. Hu, Meng,et al. [21] proposed dynamic hand gesture recognition by hidden Markov model with incremental learning. After training of the gestures, incremental learning is applied to modify the parameter of model. This makes the model more accurate for the new gestures as the data is collected.

2.4 Neural Network based hand gesture recognition

Su, Mu-Chun, et al. [22] have proposed a composite neural network for static hand gesture recognition. The authors use an EMI gloves that is connected to IBM compatible PC via Hyper Rectangular Composite Neural Network. Composite neural network uses supervised decision directed learning (SDDL) algorithm to matching with the hand gesture. Oniga, Stefan, et al. [23] used Artificial Neural Network (ANN) that are implemented in FPGA for static hand gesture recognition. The author use $5DT5$ sensory gloves to capture input data that can detect hand direction and the five fingers. Two levels of ANN are define as: (i) Feed forward ANN (ii) Competitive ANN. First one is trained using supervised learning algorithm in preprocessing step and second one is used for data classification. Modler, et al. [24] proposed a framework for music and sound control through hand gesture. They used time delay neural networks (TDNN) that is a feed forward network. For feature extraction they apply a spatial Fourier Transformation on hand gesture. TDNN network is trained by feature extracted from this Fourier Transformation. In [25] Wei, Jinwen, et al. proposed a new hand shape with the help of touch pad sensor. Touch pad senses the touching of the finger and whenever touching occurs, touching signals and position are recorded. Status of combination of fingers give features of hand shape images. Then, these instruction are sent to the hand shape recognition (HSR) system. Here, ANN is used as a classifier and input to the HSR is extracted features. Sigmoid function is used for training of the neurons. Neto, Pedro, et al. [26] used data gloves as a input device. ANN was used for static gesture classification in robot application. Each frame from data gloves is passed to the ANN. ANN is a feed forward neural network with hidden layer and output layer. Output of each neuron at output layer corresponds to each gesture.

Stergiopoulou, et al. [27] proposed self growing and self organizing neural gas (SGONG) network. Firstly, hand region are segmented by color based techniques like skin color detection algorithm. Once the hand region is segmented neural network is applied.

Output neurons output the palm and finger characteristics. These characteristics helps in identifying the open fingers. Then, in last likelihood-based classification recognize the hand gestures. Hasan, et al. [28] proposed hand gesture recognition in three steps preprocessing, feature extraction, neural network classification. In the preprocessing steps segmentation of hand, noise reduction and edge detection done. To find the most relevant characteristics of hand geometric feature like hand contour and general feature are extracted. Then three layer neural network gives the classification of static hand gestures. Output of each neuron corresponds to each gesture.

2.5 Finite State Machine based hand gesture recognition

M.Yeasin, S.Chaudhuri [29] proposed a dynamic hand gesture recognition using finite state machine. In this technique they use only a subset of hand gestures. These hand gestures are: come closer, go far, move right, move left. A finite state automation models constructed for these gesture. Gesture recognition method have two module (i) signature extraction (ii) comparison of extracted signature. In signature extraction to extract the signature they first segment the data into a sub parts which gives the motion in only one direction. The description (U/D/R/L) which they find in previous steps to get the signature are combined together. In interpretation of the signature, they derive a production rule for finite state machine. Then they check whether the extracted signature matched to which production rule thus, it identifies the gesture.

Li, Zhi, and Ray Jarvis [30] proposed a real time hand gesture recognition. They used range cameras to capture the input data and depth map. Depth map are used to extract the hand and locate it into 3D space. Chamfer matching is used to find the similarities between input hand and template. Then, 3D hand trajectories are found by finite state machine (FSM). Every hand gesture is a sequence of state transition. Whenever any new gesture comes state transition decides on which state the gesture will go to. Aksa, Alper, et al. [31] with the help of hand gesture, propose a virtual mouse system. This paper is divided in three modules. Skin detection used for extracting the hand from gesture. Some pre-processing like histogram back projection is used to improve the histogram of the hand. Then, feature extraction techniques like hull creation and defect finding are used to extract the relevant feature from hand. For posture recognition distance classifier method are used. Then, recognized hand postures are implemented as a state in finite state machine (FSM). Then FSM are used to recognize various other hand gesture. Hong, Pengyu,et al. [32] also used state machine for hand gesture recognition. Lian, Shiguo, et al. [33] proposed a hand gesture based automatic TV control system. Camera based gesture recognition activates only when low cost sensor detects the face of person whether person watching a TV or not. Then user states are recognized by finite state machine states whether person watching a TV, controlling a TV or absent.

2.6 PCA, Gabor Filter and SVM based hand gesture recognition

Huang, Deng-Yuan, et al. [34] proposed a framework for hand gesture recognition using support vector machine (SVM), gabor filter and principal component analysis (PCA). Gabor filter is combined with input images and gives a relevant feature for hand gesture. Then, the authors use PCA to reduce the dimensionality of feature space. SVM classifier is trained using these features from the feature space. SVM classifies the hand gestures between different classes. Dardas, et al. in [35] proposed a framework for interaction with video games and application with the help of hand gesture. They used skin color model to detect the hand. Then, the authora use SIFT algorithm to extract the desirable features from the training hand gestures. Vector quantization techniques with k-mean clustering are then used to combine the training image features into a histogram that is called as bag of words. These vectors form the input to the multi class support vector machine (SVM). During the testing after processing each frame, each frame is mapped with the bag of word and then fed to the SVM to classify the hand gesture.

Dardas, Nasser H, et al. in [36] uses PCA for hand gesture recognition. Hands are detected by skin color model and contour comparison algorithm. In the training hand posture with different orientation, position and scales are trained and Eigenvector of training images are obtained. Then, training weight for each is computed with the help of Eigenvectors are determined. During the testing phase, hand is detected in each frame and with the help of training Eigenvectors, the test weight are calculated for each frame. Once test weights are calculated minimum Euclidean distance between test and each training gesture weight are determined. Then hand gesture having minimum distance are recognized. Gupta, et al. [37] used gabor filter for feature extraction. Feature extracted by gabor filter are very high dimensional feature. So PCA and LDA both are used for dimensionality reduction. SVM used to classify the hand gesture.

Trong-Nguyen Nguyen et al. in [38] proposed a framework for sign language recognition using artificial neural networks and PCA. Authors used single camera to collect the data set. Background subtraction and skin detection algorithm used to extract the hand from large input image. Median filtering, local binary pattern and histogram of gradient (HOG) are used to improve the detection accuracy of hand. Principal Component Analysis (PCA) is used to extract the features of detected hand. In last multiple layer perceptron network (MLPN) used for testing and training of hand gesture.

2.7 Hand gesture recognition system using geometry based normalizations and Krawtchouk moments

Priyal, S. Padam, and Prabin Kumar Bora in [39] divide the gesture recognition process into three modules (i) Extraction of hands from forearm (ii) rotation, normalization according to gesture orientation (iii) robust hand gesture recognition according to view and user dependent. Gestures are detected by skin color and segmented to obtained the binary silhouette. Krawtchouk moment features are used to represent the normalized binary silhouettes and classified using a minimum distance classifier.

2.8 Hand gesture recognition based on Dynamic Bayesian network framework and weighted elastic graph matching

Suk, Heung-Il, et al. [40] use dynamic Bayesian network to recognize the hand gesture from continuous video streams. Skin modeling and motion tracking are the steps for DBN processing. Firstly, the authors develop a model for one or two hand gestures that are used for cyclic continuous gestures module. Author also develop decoding algorithm for recognition of continuous hand gestures. Li, Yu-Ting, and Juan P. Wachs. [41] author use elastic graph matching for hand gesture recognition. Weights are assigned to each visual feature according their distinction property of hand gesture. Adaptive boosting algorithm are used to assign weights on elastic graph. Bunch graph defines the variability of each gesture class. Semi automatic methods defines the position of nodes on elastic graph matching. Node annotation techniques and weighting scheme on features are used to classify the hand gesture.

Chapter 3

Proposed Approach

In this thesis, we propose a framework for automated hand gesture recognition from an images using depth data and unsupervised learning. Automated recognition of hand gestures helps in making man machine communication natural and finds application in different areas like gaming, human computer interaction HCI and assistive living.

We propose to use the Kinect sensor device for capturing the hand gesture. Kinect sensor captures the RGB image and corresponding depth map. Depth map is the corresponding depth data of the scene that depends on the distance of the scene object surfaces from the camera's viewpoint. The hand is assumed to be closest to the camera and therefore, we propose to use the depth data to extract the hand information from the images.

3.1 Our Proposed Model

Our complete hand gesture recognition system is divided into different module. These steps are shown in below model.

In our hand gesture recognition framework, we focus on static hand gesture. Static hand gesture refers to the static shape of the palms and fingers that expresses some meaning for communication.

We also assume that the gesture is defined by the shape of the hand, mainly the

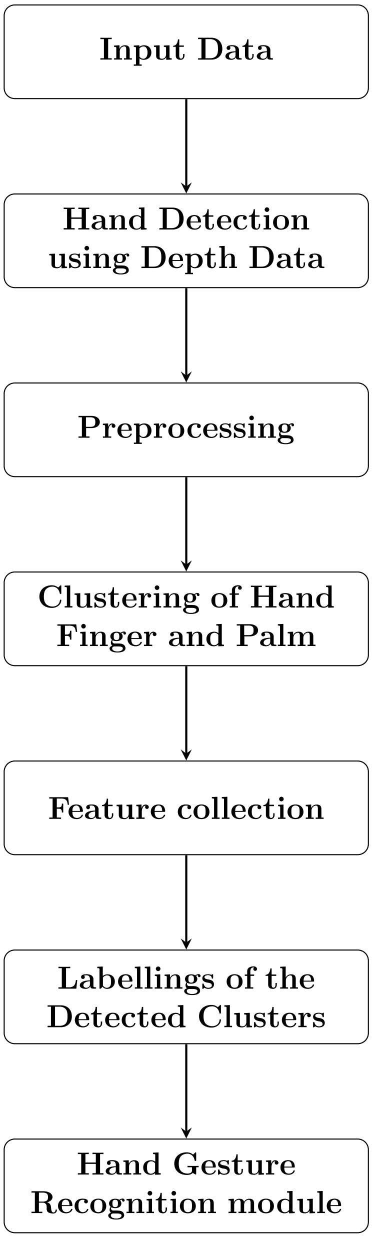


Figure 3.1: Flowchart of proposed Hand Gesture Recognition System

number of open fingers, which fingers are open, orientation of hand etc. We do not differentiate between the various orientation of the hand for recognizing a gesture and focus only on the shape of hand.

The **Input data** contains RGB image and corresponding depth map of each gestures. Few examples of data set, RGB and corresponding depth images are shown in Figure 3.2 and Figure 3.3 respectively.

Figure 3.2: Rgb image

Figure 3.3: Depth image

3.1.1 Hand detection using depth data

In this we used depth image to detect the hand from input images. As hand is a very small object compare to the body, it's difficult to detect hand but with the help of depth information we are able to detect the hand. We extract the hand from depth image by giving some depth value ranges which are obtained experimentally. These ranges are not exact range but decided experimentally. We extract the image portion of this range and stored in RGB form. Thus hand gestures are easily segmented. Some results of this steps are shown in Figure 3.4. We only require the pixels containing

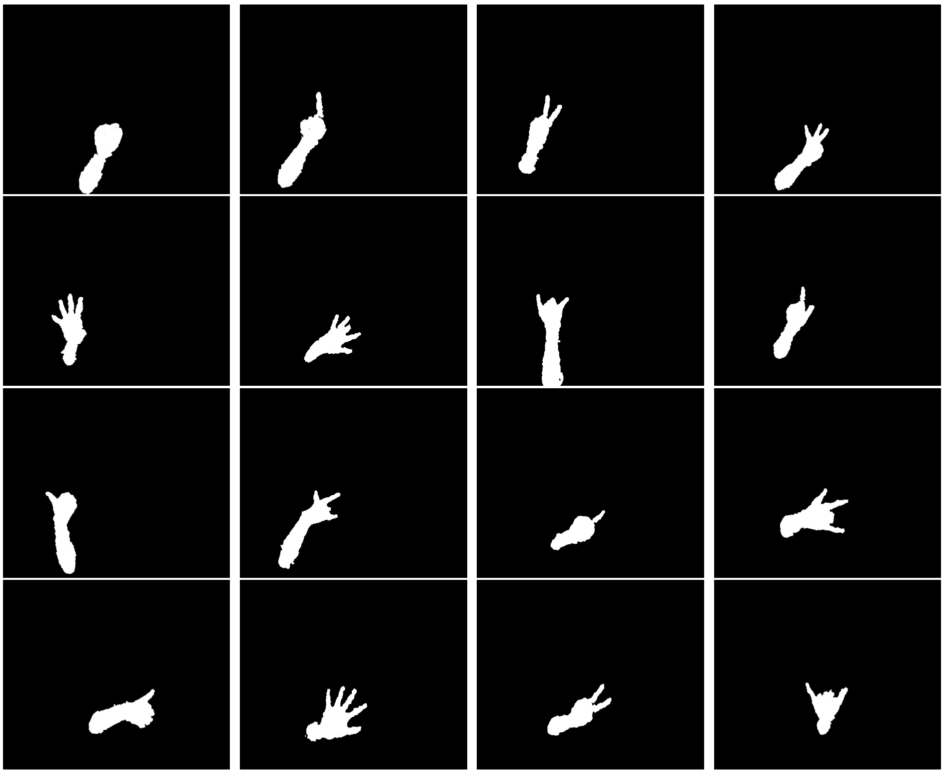


Figure 3.4: Detected hand gesture from depth image

the gesture information, therefore in the next step, we detect the boundary of the hand gesture and remove all other parts of the images. This also reduces the amount of data to be processed thereby helping in making the system real time.

3.1.2 Preprocessing

Since we do not differentiate between hand gestures based on orientation of the hand, we first change the orientation to the vertical in all the cases. To do so we first find the orientation of the segmented hand. We apply principle component analysis [46] to the segmented hand and find the angle of the major axis. We then perform a rotation with respect the vertical axis of the hand data using this angle. This ensure that our next steps is correctly performed.

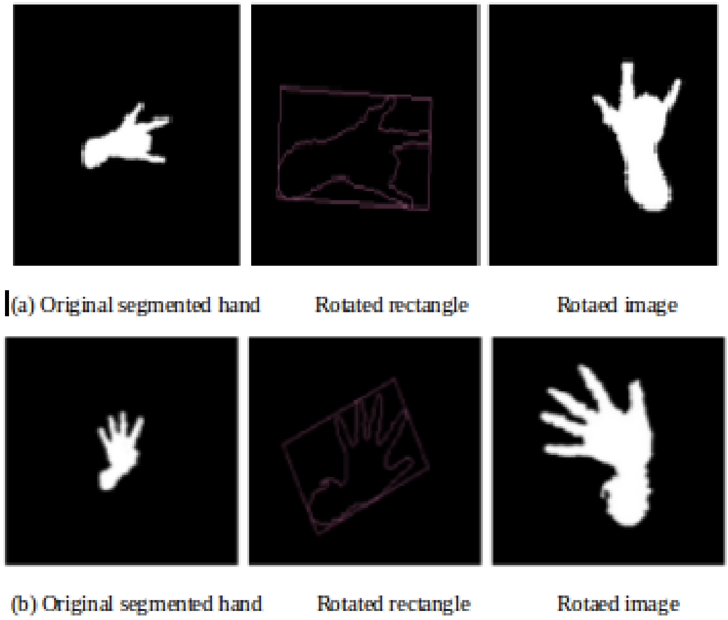


Figure 3.5: Rotated Image

In the Figure 3.5 (a) is our original segmented hand image. In (a) rotated rectangle image we find the rotated rectangle using PCA on detected hand contour and find the angle of major axis. In (a) original image is rotate by the angle that we got by PCA. Same process we apply rotation on all the detected hand gestures. Figure 3.5 demonstrated the step involved.

As mentioned earlier, we work with the cropped hand image therefore, after rotating the images, we crop it using the bounding box of the detected hand. For this first we draw the bounding box around the hand and then cropped that bounding box. Results of this step is shown in Figure 3.6

In Figure 3.6 1st and 3rd row are fitted bounding box hand frame and 2nd and 4th rows are cropped bounding box hand gestures respectively.

3.1.3 Clustering of hand fingers and palm

We need to know the shape of the hand, since the static hand gestures are depend on the shape of the hand. Specifically we need to know the number of fingers that

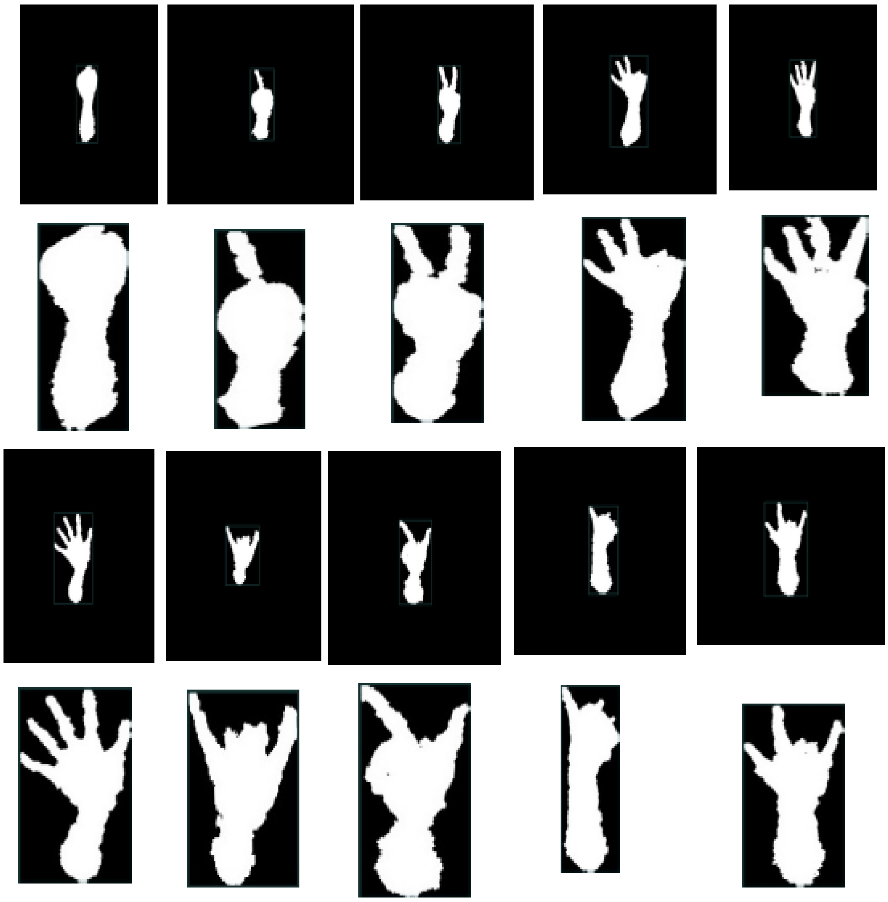


Figure 3.6: Cropped hand gesture

are open, which fingers are open, this define the differentiating features between hand gestures. We propose an unsupervised learning based algorithm for finding the various fingers in each hand gestures. Based on this we also label the fingers that are open.

In this module we divide the single hand images into number of clusters. Suppose we have five finger gesture, thumb will go in one cluster, index finger will go in another cluster, little finger will go in another cluster, palm will go in another cluster, wrist will in another cluster and so on. As we know our detected hand is a only black and white pixel. White pixel is detected hand gesture and black pixel is a background part. This type of images are shown in above Figure 3.6

In our clustering algorithm,

- we cluster hand gestures using the values of the pixel, since we know that 1 defines part of the hand and 0 is background. Our clustering strategy is using continuity of white pixels and the thickness parameter.

- This gives us various clusters of the different fingers if they are separated. It ensures that the open fingers are correctly detected.

- For visualization, we display each cluster with different color.

The results of above algorithm have been shown below in Figure 3.7. Figure 3.7 (a) is

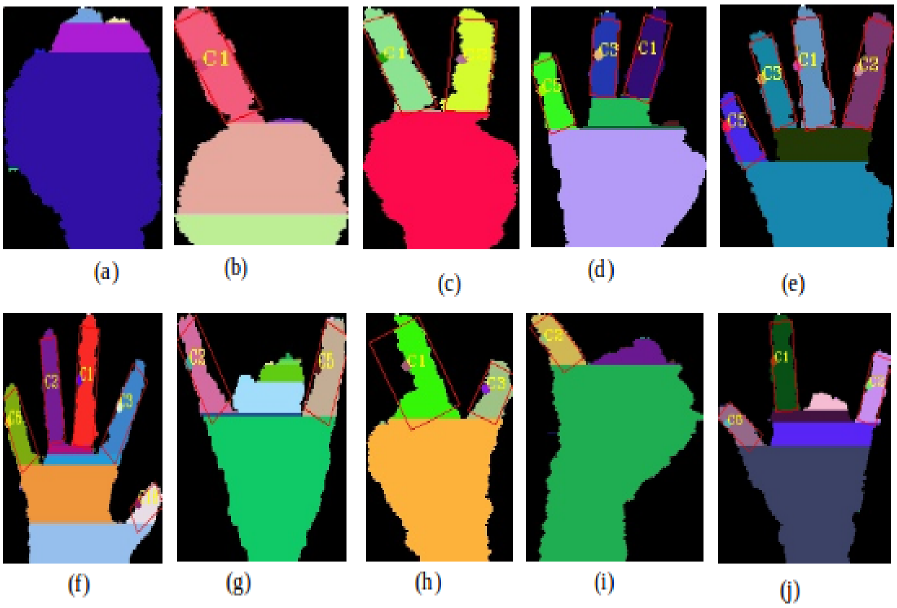


Figure 3.7: The image (a) to (j) various clusters formed in each image using our proposed clustering algorithm

a fist. In Figure 3.7(b), there is only one finger and whole hand is divided into a three major clusters and some minor clusters. Like this hands are divided into different parts and we can separate the fingers and thumb from palm. Cluster numbering c1,c2 and so on, these are random clusters name. After clustering we start counting the number of open fingers so that we can easily recognize the gestures with the help of open fingers only. Rather than matching on the whole hand we start with matching the fingers. This will reduces the recognition time by a large amount. To be able to recognize using the open fingers we extract various features of these fingers in the next step.

3.1.4 Feature Collection

In feature extraction step we collect the following features.

- Number of open fingers.
- Euclidean distances between fingers.
- Orientation of fingers.
- Thickness of fingers.
- Length of the fingers.

In the **Number of open fingers** we assume that those clusters that have a certain thickness and length, defines an open finger. With the help of thickness of cluster and length of cluster we count the number of open finger. Experimentally we decide the thickness and fingers length range.
Once the number of open finger is determined, we start finding the euclidean distance between all the open fingers. Distance is calculated from thumb to all other fingers, index fingers to all other fingers and so on.
In the **orientation of finger** we start finding the orientation of fingers and thumb from x-axis. Again we use the PCA on each cluster representing an open finger to find the orientation and also draw a bounding box around those for clear visualization of oriented clusters.
Thickness of fingers are determines by averaging cluster width corresponding to each fingers.
Length of the fingers are determines by cluster length corresponding to each fingers. Extracted features of this steps are shown in Figure 3.8, 3.9 & 3.10

3.1.5 Labeling of the Detected Clusters

After clustering and feature extraction we start numbering of the fingers and thumb. We take two features, distance between fingers and orientation for labeling of fingers. In the cropped bounding box if there is a either thumb or little finger is open, then

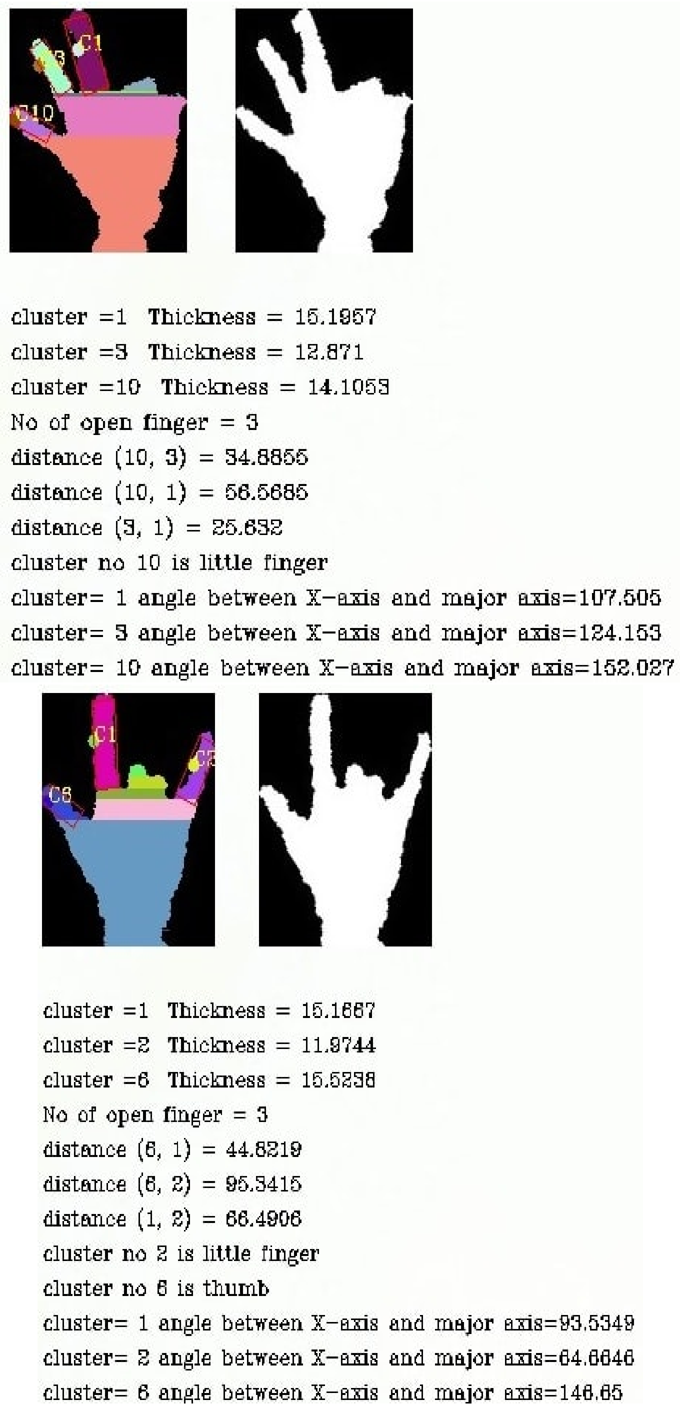


Figure 3.8: Extracted Features

we can identify the little and thumb finger because thumb and little finger will touch the boundary of bounding box. For five finger gestures we consider only orientation of fingers for the labeling. For two finger gesture we consider distances for labeling.

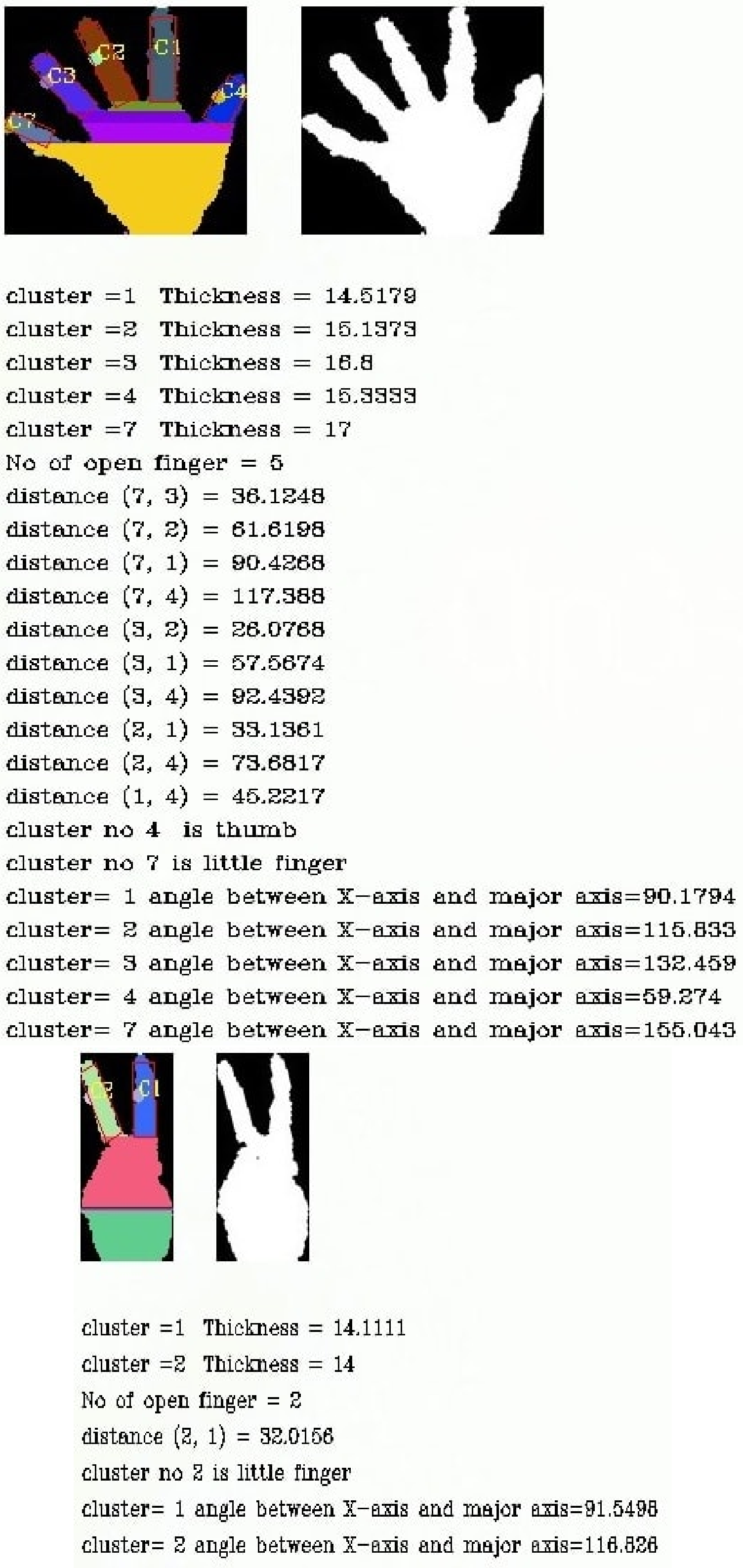


Figure 3.9: Extracted Features Continued

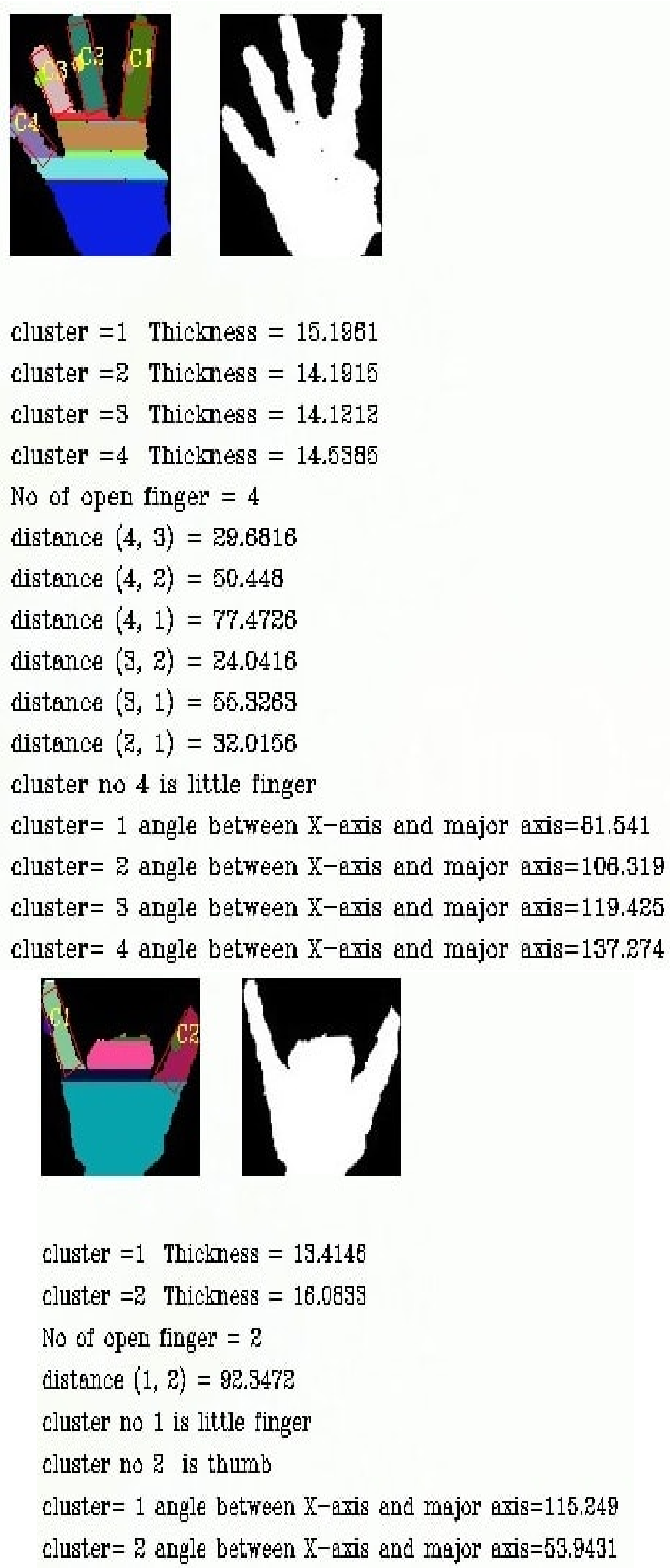


Figure 3.10: Extracted Features Continued

We give the label F1 to thumb, F2 to index finger, F3 to middle finger, F4 to ring finger, F5 to little finger. Figure 3.11 shows the results of detected finger's with their

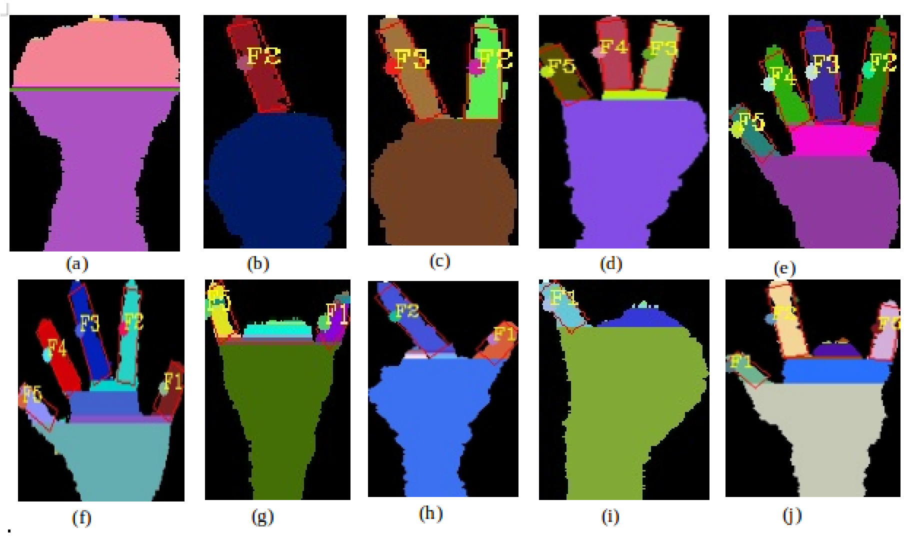


Figure 3.11: Finger Name

labels. Using all these features now we can recognize the input hand gesture.

3.1.6 Hand gesture recognition module

Now we have the finger data and the features extracted from open fingers. We divide our complete data set into test data and training data. We find the average values of each features for training set of each gesture. We use this as a template of each gesture. We compare the test data with this template to recognize the hand gesture with high accuracy. Averaging values of the gestures are in Figure 3.12 and 3.13.

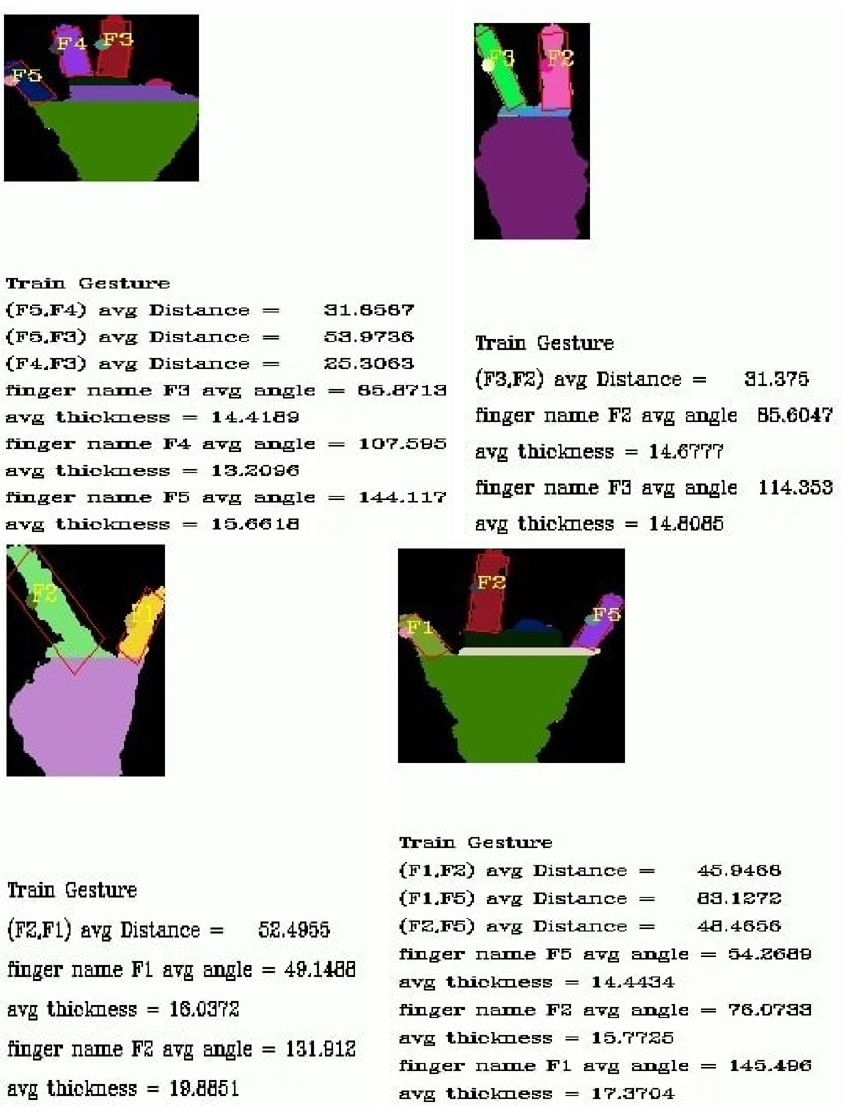


Figure 3.12: Average values of training hand gestures

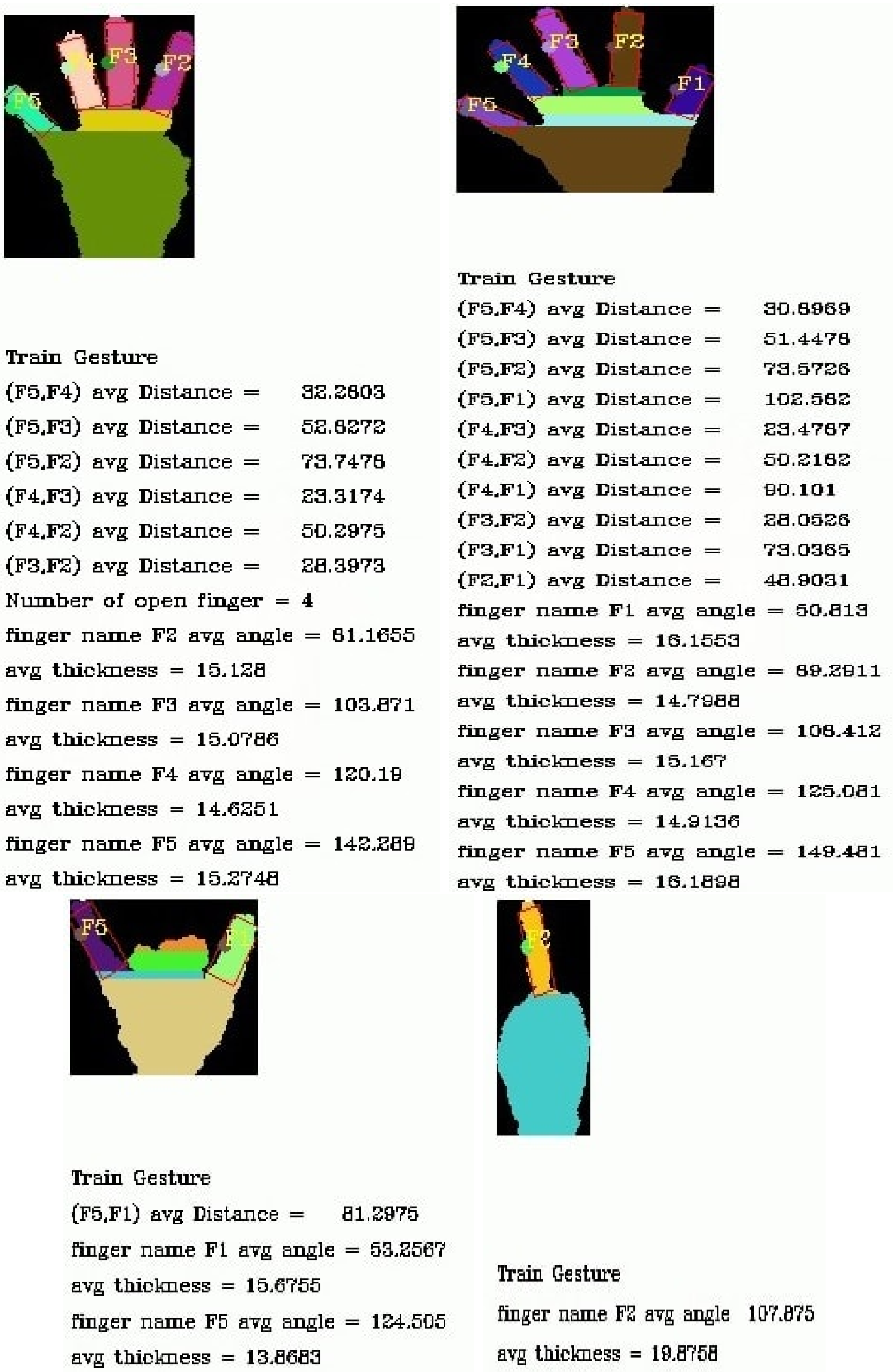


Figure 3.13: Average values of training hand gestures

Chapter 4

Experimental Results

In this chapter, we explain the outcome of our proposed hand gesture recognition system. First, we divide the complete hand gestures into test and train hand gesture. We have total 80 hand gesture for training and 20 hand gesture for testing. We find the average of the feature of 80 hand gestures. We find average distance of each fingers, average thickness of each fingers, average angle of fingers and thumb orientation. These average values are use as a template for matching with test hand gesture. For each test hand gesture we need to match total 80 hand gesture. We have total 10 different test gesture and each test gesture have 20 gesture. Thus total test hand gesture is 10*20= 200. In same manner we have total 10 different train hand gesture and each train hand gesture have total 80 gesture. Total training hand gesture is 10*80=800. Each test hand gesture will match to each training gesture and total 20*80*10*10=160000 matching occur.

This will take lot of processing time. Thus, due to averaging of 80 training hand gesture features, we do not need to match each training hand gesture to each test hand gesture. Each test hand gestures will need to match only average features of hand gesture. Thus, 20 test hand gesture will match to only 10 different hand gestures average values. Therefore total matching reduces to 200*10=2000. This makes our system very fast and real time.

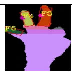
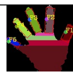
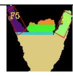
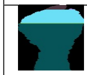
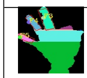
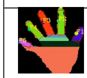
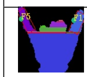
During the matching of two hand gesture, we calculate the distances between those two hand gestures. Distance between two hand gestures is our recognition criteria. We calculate the difference in terms of distance corresponding to each fingers and then find the average. This gives us a distance between hand gestures. Experimentally we obtain the threshold value of 10. If the distance between two hand gesture greater than the threshold value it implies that the test gesture and training hand gesture do not match. If distance between the hand gesture is less than threshold that means test hand and training hand gestures are same.

Our recognition system first checks number of open fingers are same or not. If number of open fingers are not same then matching process stop here and returns that both gestures are not same. Our system also returns average distance between both gestures that is higher than the threshold. If number of open fingers are same then matching process further matches the finger's name. If fingers name are same then both gesture would be same and it processes further otherwise it returns that both gesture are not same & returns average distance between test and train hand gesture. If finger names are same and average distance between test ans training hand gesture is with in threshold our system returns a match otherwise no match.

In our recognition process we consider the number of open fingers, labellings of fingers, distance between hand gestures for recognizing the hand gesture. We do not differentiate between the various orientation of the hand for recognizing a hand gesture and focus only on the shape of hand. In case if we need to consider the orientation of hand gesture, we will do matching on the angle of the hand that we got in preprocessing step.

Our matching results are shown in the Table 4.1. Column contains the training images of 10 different hand gesture and rows contains the test images of 10 different hand gestures. Numeric entries in the Table 4.1 is our recognition criteria (Distances between training and test hand gestures). Each gesture of rows will match to the each column gestures. We perform matching on the complete hand gesture and few results are shown in Table 4.1. In the Table 4.1 Na entries means distance between test and training hand gestures has not been calculated because the gestures has either one open finger or no open finger. On our proposed work matching is done

Table 4.1: The table entries represented the distance between hand gesture in each of the 10 different gestures in our data

		Training Images									
											
Test Image		0	Na	Na	Na	Na	Na	Na	Na	Na	Na
		Na	0	31.375	36.046	43.47	57.229	81.28	52.19	17.42	59.179
		Na	32.01	.54	26.47	38.142	54.25	49.25	20.47	14.01	48.05
		Na	39.02	28.57	0.46	26.67	47.34	42.67	33.27	29.74	20.15
		Na	44.63	401.5	28.10	2.03	37.47	48.46	43.66	41.92	31.55
		Na	62.12	60.23	52.25	42.12	2.1	64.27	61.39	60.91	51.66
		Na	78.10	62.54	47.14	48.36	60.65	.20	41.52	76.59	54.09
		Na	53.03	34.36	37.54	43.63	57.6	15.77	4.39	39.45	50.68
		Na	Na	31.37	37.04	43.47	57.72	81.29	52.49	0	59.19
		Na	67.15	56.05	30.11	27.42	18.15	62.61	53.21	60.64	4.5

on the basis of number of open finger and distance between hand gestures. If open fingers are not same then it automatically gives result that both hand gesture are not same and no need of further checking. Entries at (row,col)=(1,1) & (2,2) & (9,9) is zero there is either one open finger or fist therefore, distance between fingers has not been calculated.

All the entries that are colored in red is a recognition rate with same hand gesture and all other entries is a recognition rate with different hand gestures. Those entries are marked in red have less distance compare to all other it means hand gesture is correctly recognized and less than the threshold values. Some hand gesture have very good recognition rate like in (3,3), (4,4), (7,7) distances are .54, .46, .20 respectively. When number of open fingers are same, it starts matching with the finger name whether the the fingers are same or not. Like in Table 4.1 entry (4,10) number of open fingers are same but open finger in row 4 image is middle, ring and little finger and in column 10 image is thumb, index and little finger. Therefore both hand gesture are not same and distance between these gesture is 20.15 that is higher than the threshold values. Its results are shown in Figure 4.1.

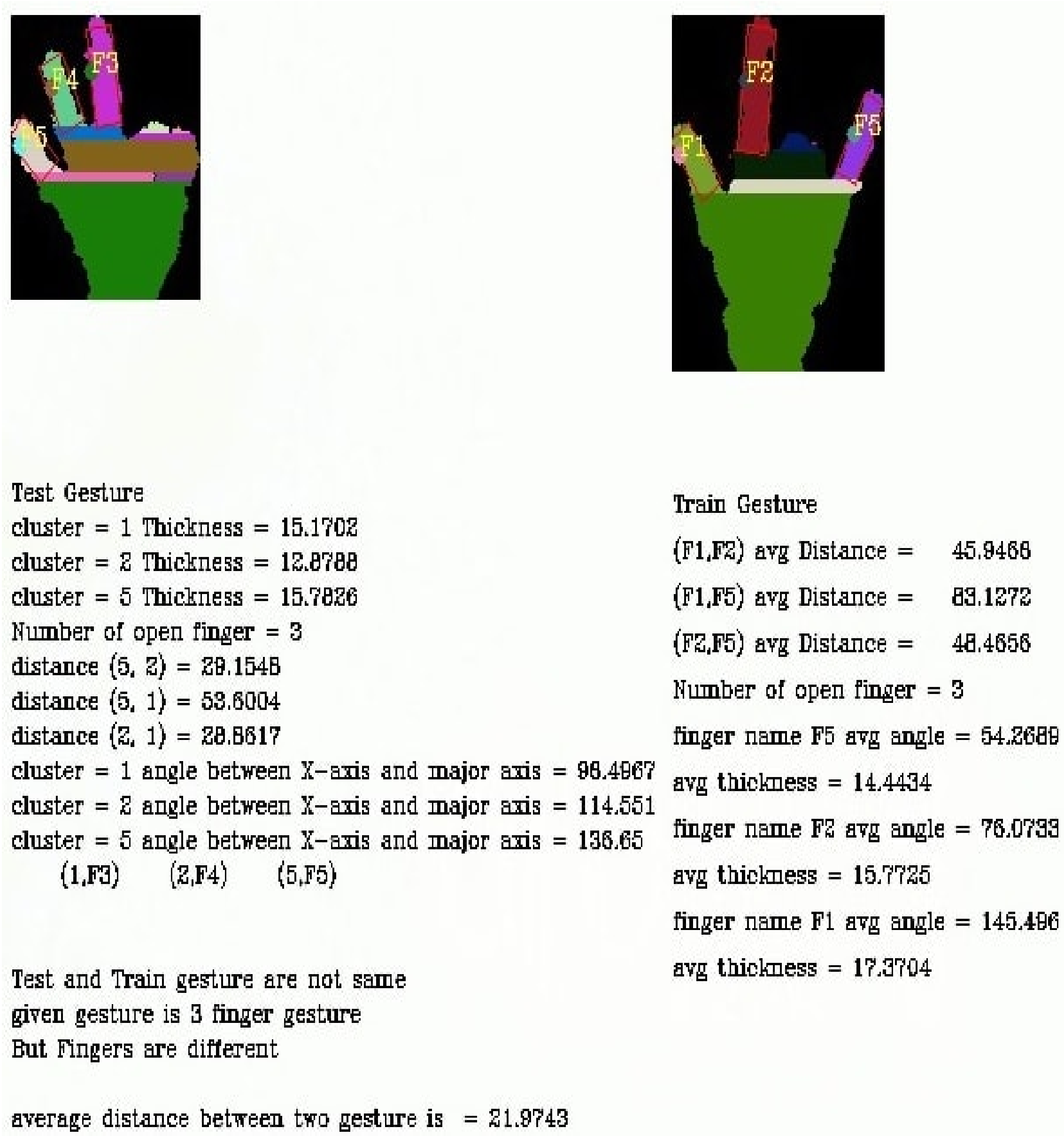


Figure 4.1: Both hand gestures are different but number of open fingers are same. Our system first check that number of fingers are same then it further checks the labeling of the fingers, the labels of fingers are not same and distance is 21.97 that is higher than the threshold value therefore our system returns no match.

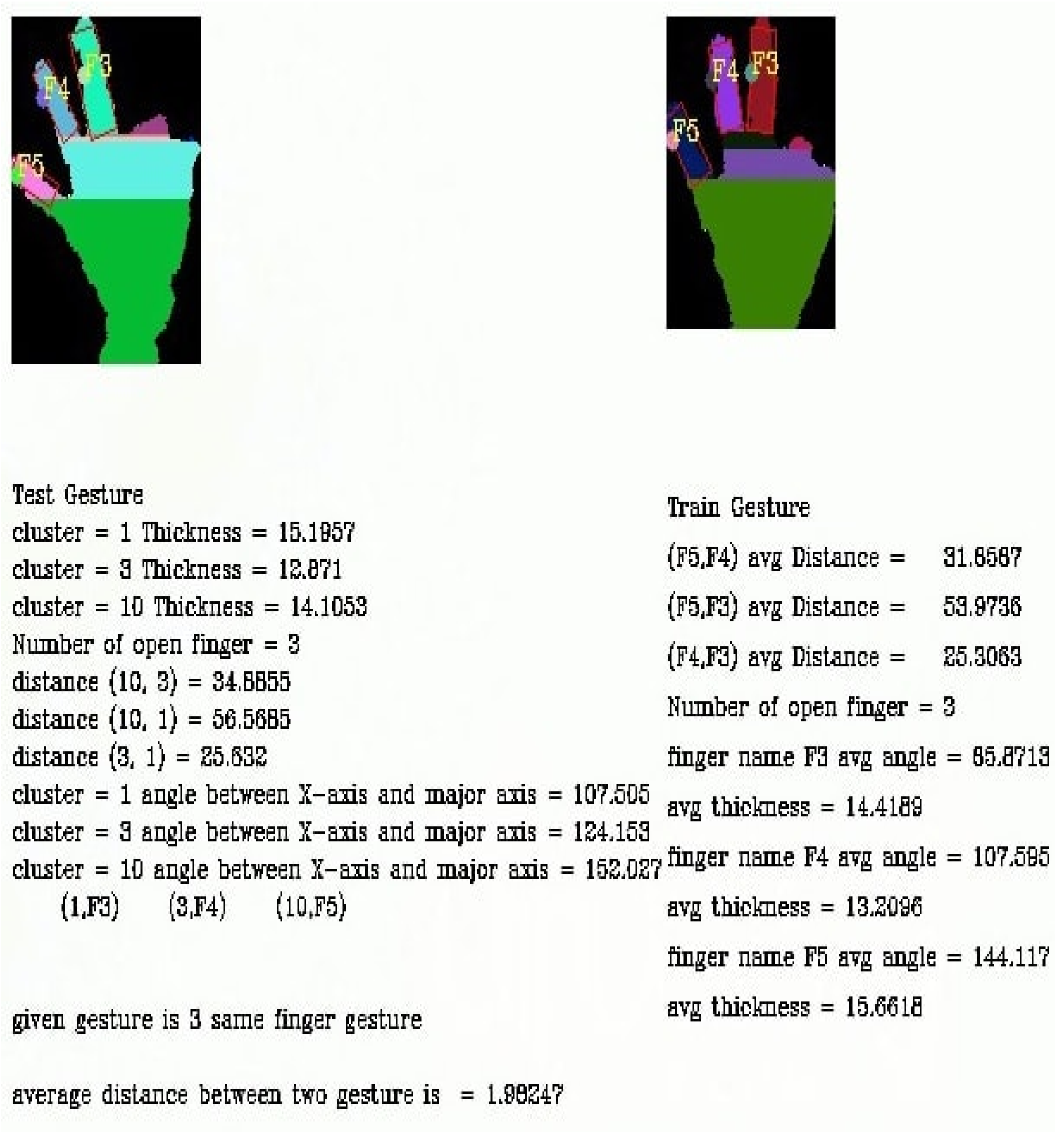


Figure 4.2: Here number of open fingers are same and labeling of fingers are also same. Our recognition system checks that number of fingers and labeling of fingers are same, system returns that both hand gesture are same and distance between both hand gestures is 1.99 that is less than the threshold value.

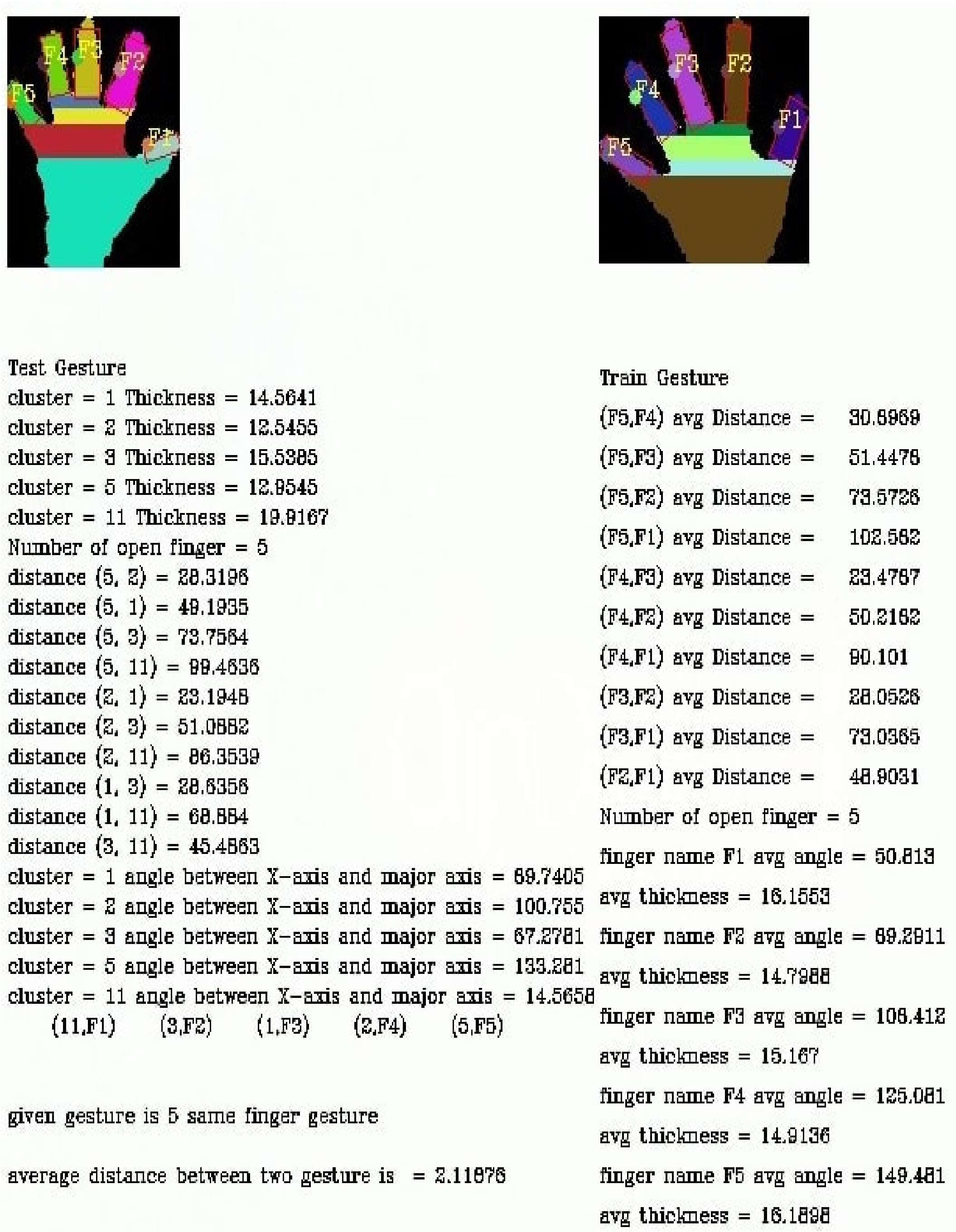


Figure 4.3: Here number of open fingers are same and labeling of fingers are also same and distance between both hand gestures is 2.11 that is less than the threshold value. Our recognition system returns that both hand gestures are same.

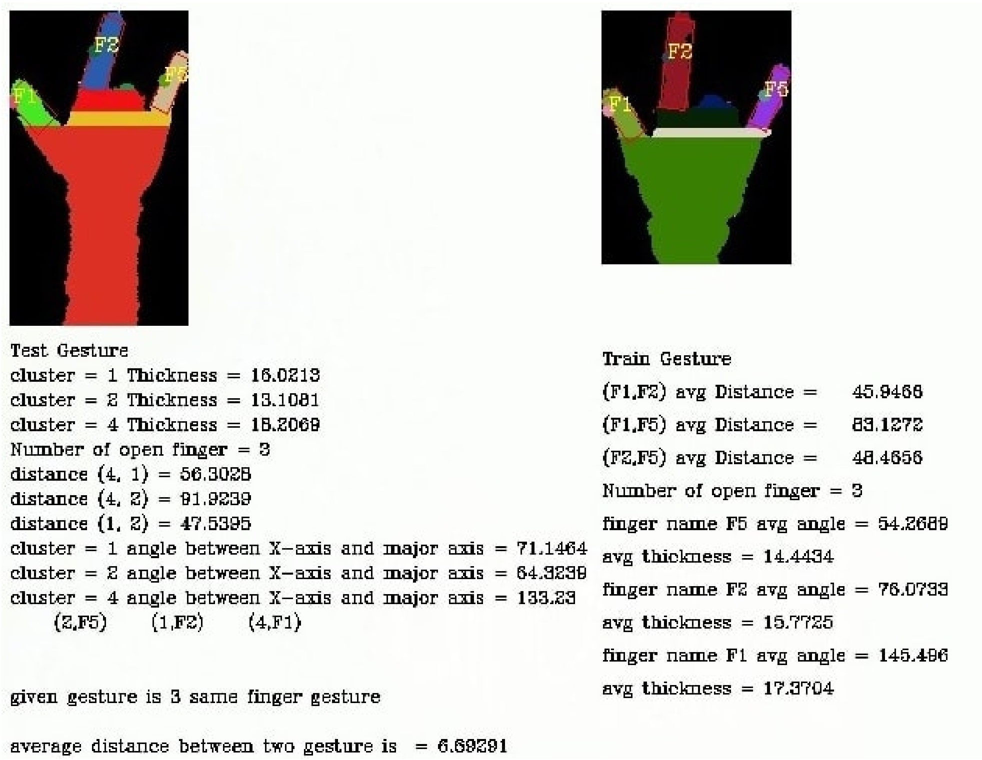


Figure 4.4: Here number of open fingers are same and labeling of fingers are also same and distance between both hand gestures is 6.59 that is less than the threshold value. Our recognition system returns that both hand gestures are same.

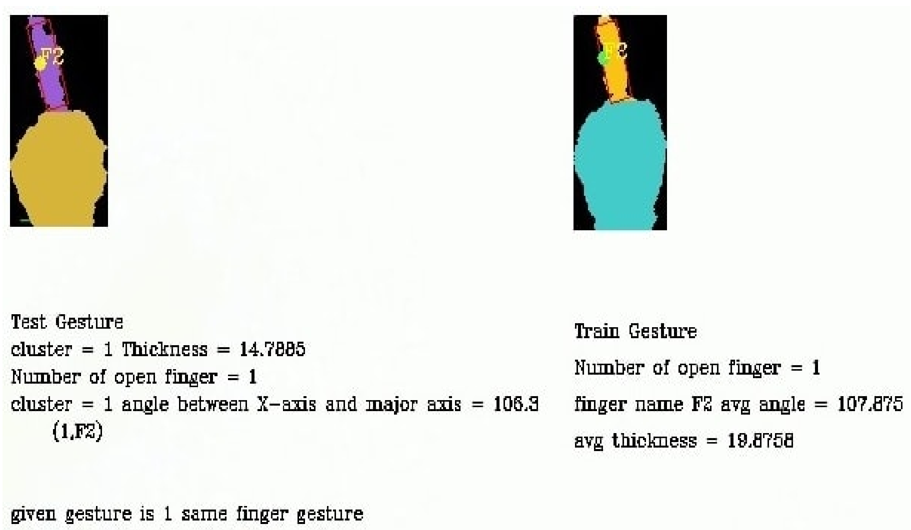


Figure 4.5: Here number of open fingers are same and the label on the finger is also same. In this gesture only one open finger therefore distance has not been calculated. Thus our system returns that both gesture are same and distance between gestures is NAN.

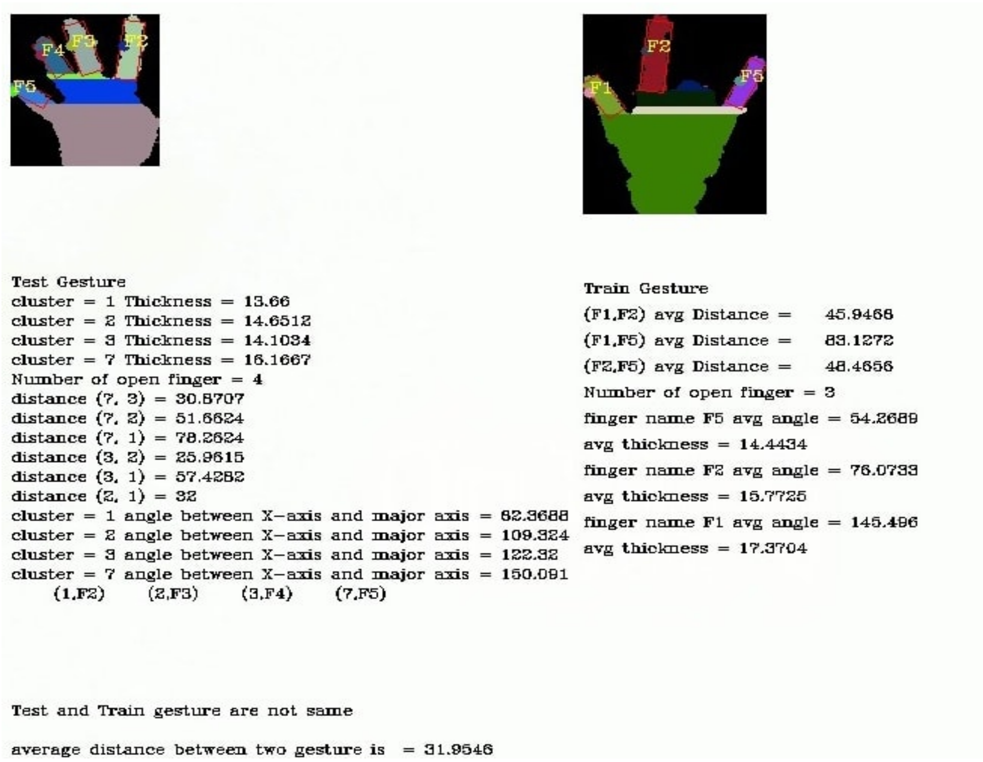


Figure 4.6: Here number of open fingers are not same. Thus system returns returns no match and distance between both gesture is 31.95 that is higher than the threshold value.

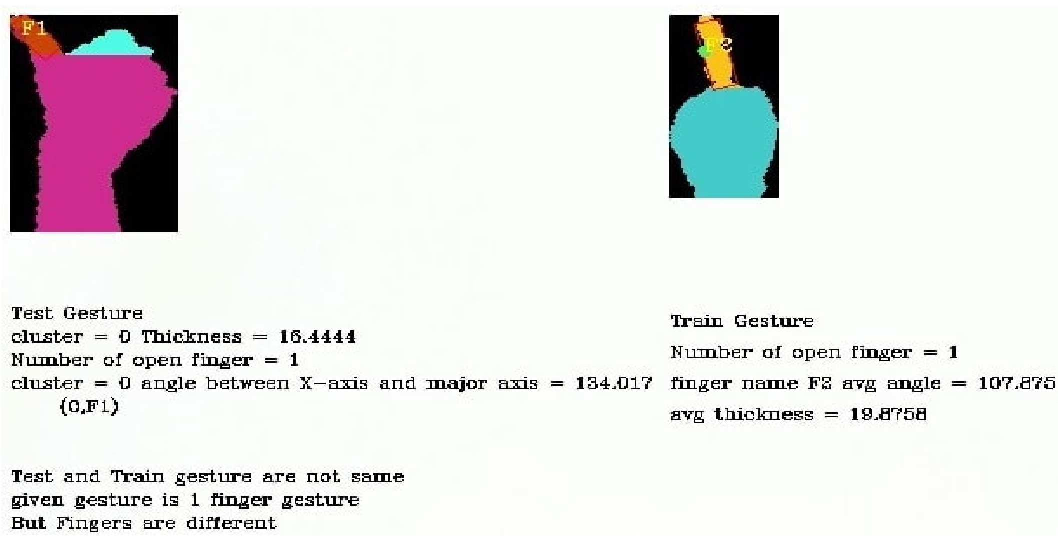


Figure 4.7: Here number of open fingers are same but label on finger are not same. In this gesture only one open finger therefor we can not calculate distance. our system returns that both gesture are not same and distance between gestures is NAN..

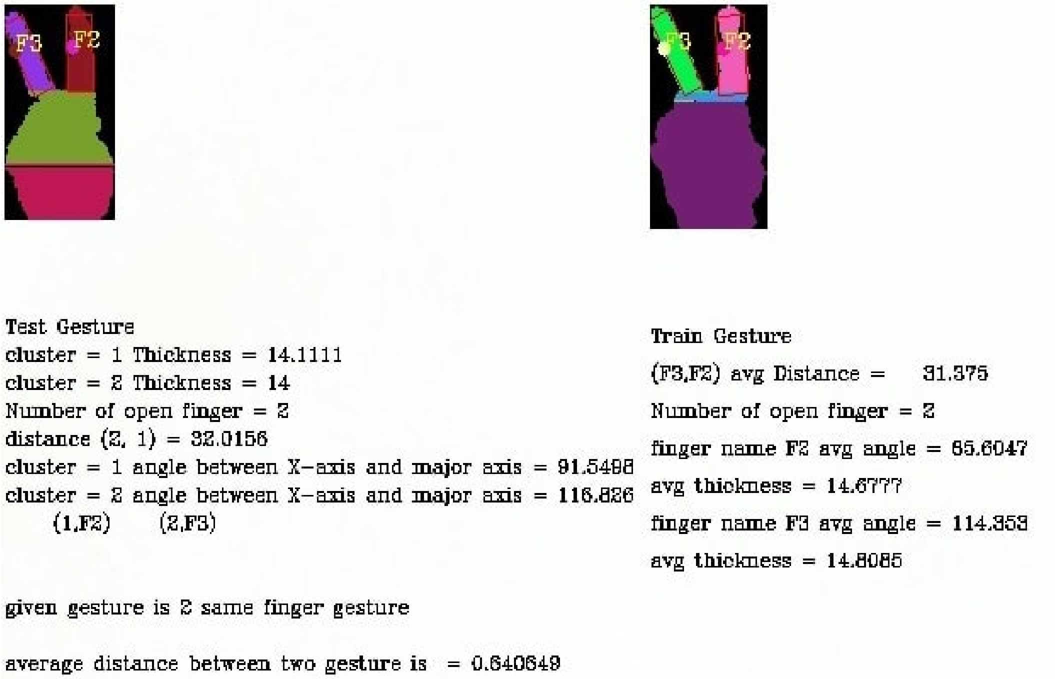


Figure 4.8: Here number of open fingers are same and label of fingers are also same and distance between both hand gestures is 0.54 that is less than the threshold value. Our recognition system returns that both hand gestures are two finger gesture.

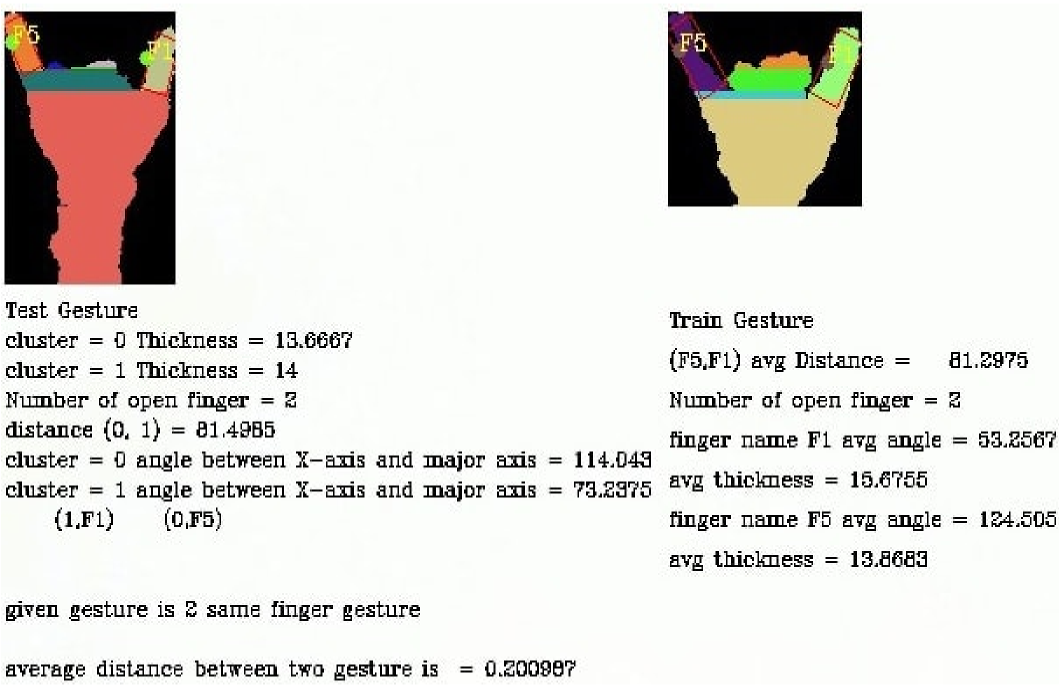


Figure 4.9: Here number of open fingers are same and label of fingers are also same and distance between both hand gestures is 0.20 that is less than the threshold value. Our recognition system returns that both hand gestures are two finger gesture.

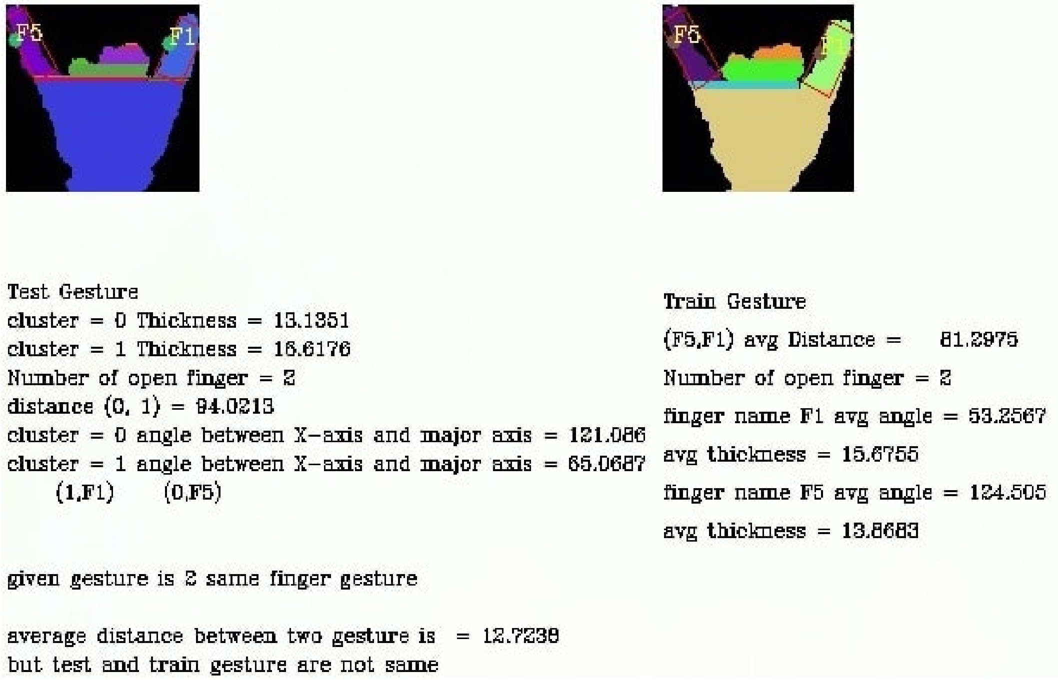


Figure 4.10: Here number of open fingers are same and label of fingers are also same. Our system returns that both gesture are 2 finger gesture but both gesture are not same and distance between gestures is 27.69 that is greater than the threshold value.

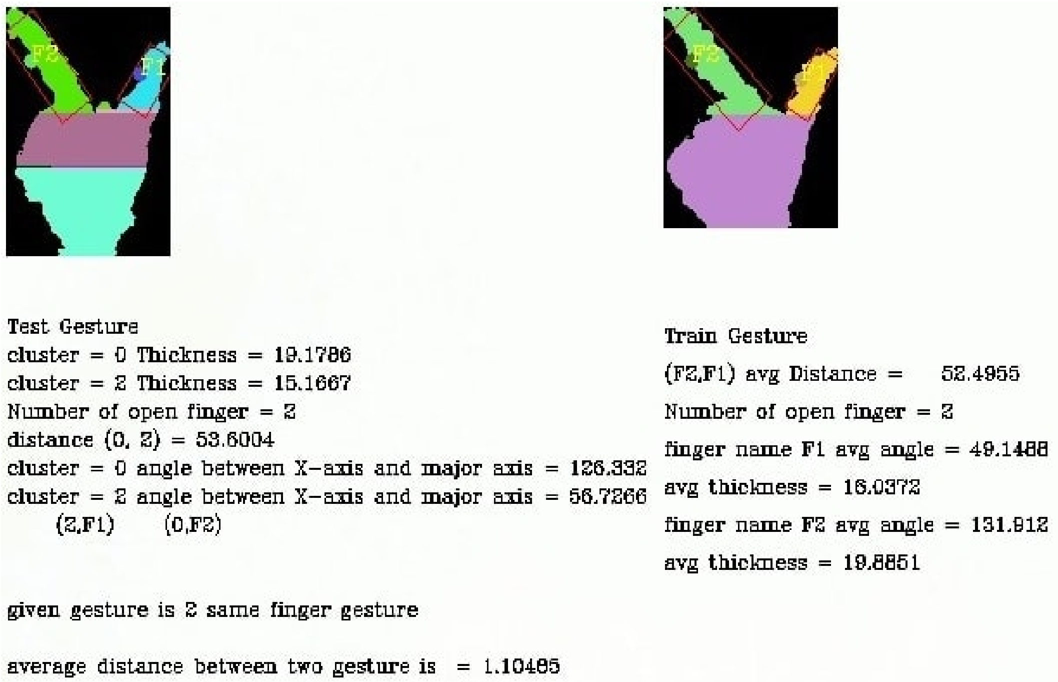


Figure 4.11: Here number of open fingers are same and label of fingers are also same and distance between both hand gestures is 1.11 that is less than the threshold value. Our recognition system returns that both hand gestures are two finger gesture.

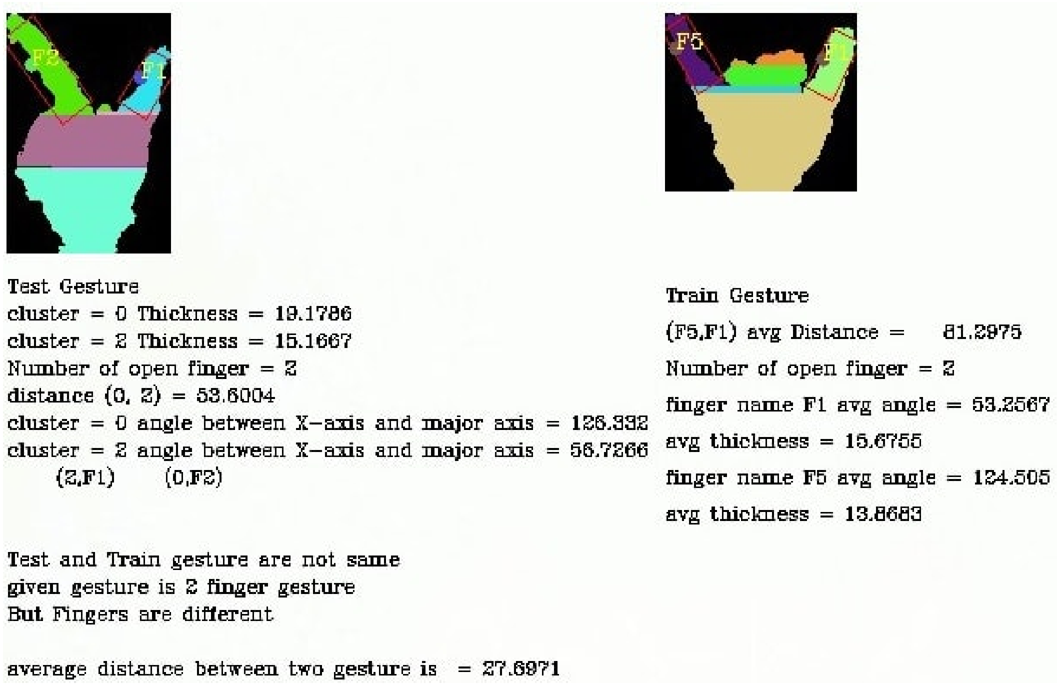


Figure 4.12: Here number of open fingers are same but label of finger are not same. Our system returns that both gesture are not same and distance between gestures is 27.69.

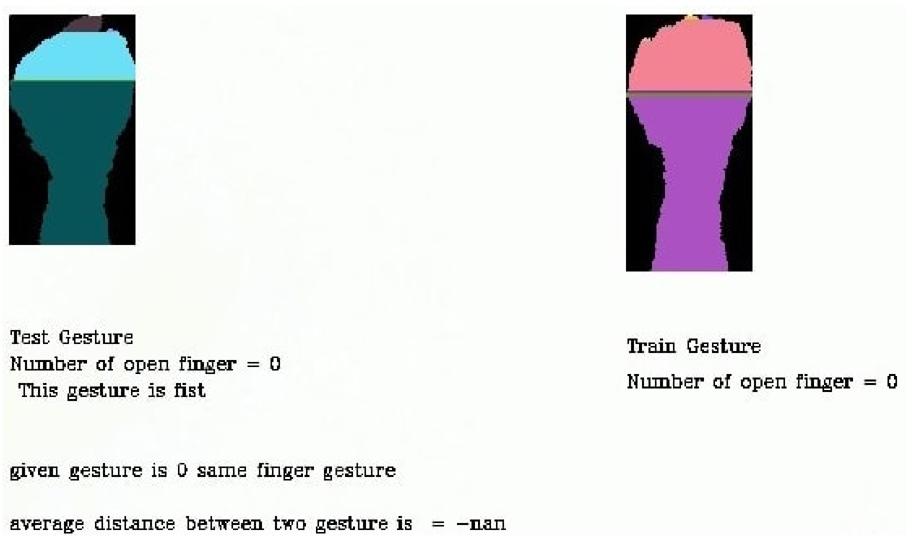
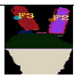
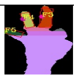
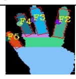
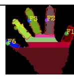
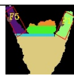


Figure 4.13: There is no open finger. Our system returns that both gesture are same and given gesture is a fist & distance between gestures is NAN.

Table 4.2: Diagonal entries in table represents the recognition rate of our hand gesture recognition system. Some times clustering may not be appropriate, distance between hand gesture is higher than threshold value, labeling of clusters may not be correct this causes failure of hand gesture recognition. Overall our recognition rate 89%.

		Training Images									
											
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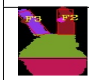
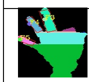
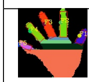
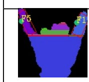
			85%								
				100%							
					95%						
						95%					
							90%				
								80%			
									80%		
										90%	
											85%

Chapter 5

Conclusion and Future Work

In this thesis, we propose an unsupervised learning based hand gesture recognition framework. We use the RGBD sensor from Microsoft called kinect to gather depth data along with RGB data. We use this depth data for detecting the hand in the image. We then, apply our incremental clustering algorithm for finding the shape of the hand in terms of the number of open fingers & the labels on these fingers. The recognition is carried out based on various parameters such as number of open fingers, their orientation and distances. Experimental result shows that our system is able to recognize these gestures correctly and is robust. Moreover our system works in real time since the test data is matched with the representation data of each hand gestures in the training set.

Automated Hand gesture recognition is a promising research area focus for designing natural and intuitive methods for human computer interaction for number of computing domains, task and applications. Hand gesture recognition enables more natural, intuitive communication between people and between man-machines.

In future we would like to extend this work for dynamic hand gesture recognition.

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