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Hand Gesture Recognition System in Electronic Device Applications

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ABSTRACT

In order to receive information people repeat same mouse and keyboard actions, inducing waste of time and inconvenience. To improve these situations, we have proposed a system in which user can interact with system by using hand gesture. Communication through gestures has been used since early ages not only by physically challenged persons but nowadays for many other applications. As most predominantly hand is use to perform gestures, Hand Gesture Recognition (HGR) methods have gained tremendous interest in the past few years. The technique of HGR allows humans to connect with the system and interact naturally, thereby avoiding the involvement of any mechanical amenities. Automatic control of home appliances in smart home is an important application of a HGR system. In this paper, we propose a new HGR system using PCA as the feature descriptor. The initial stage of classification is performed by the proposed modified Support Vector Machine (SVM) classifier. In the second stage a classifier fusion model called as hybrid ensemble classifier obtained by combining K-Nearest Neighbour (KNN) and the modified SVM classifier is used. The experimental results show that the proposed hybrid ensemble and the modified SVM classifier provides better results compared to the individual classifiers.

Keywords: SURF, BoF, KNN, Modified SVM Classifier, Hybrid Ensemble Classifier

1. INTRODUCTION

Gestures are the movement of any body part used to convey the meaningful information. Communication through gestures has been widely used by humans to express their thoughts and feelings. Gestures recognition refers to the process of identifying gestures performed by human so that machine can perform the corresponding action. Gestures have been classified in two categories static and dynamic. Static gestures refer to still body posture and dynamic refers to movement of body part. Gestures can be performed with any body part like head,face, arms, hands, etc. but most predominately we use hand to perform gesture like we wave hand to say 'good bye'. Hand gestures have been widely used for many applications [like human – computer interaction (HCI), robotics, sign language, human machine interaction, TV interaction etc. With the advancement of technology, human robot interaction (HRI) has become an emerging field in recent years. Hand gestures can be effectively used to give commands to the robot which in turn can be employed in large number of applications.

Now-a-days, human robot interaction using hand gestures has widely been used in medical sciences. But still challenges regarding robustness and efficiency are to be considered. Hand Gestures Recognition techniques have been divided into two categories. Sensor based and Vision Based recognition. Sensor based recognition collects the gesture data by using one or more different types of sensors.These sensors are attached to hand which record to get the position of the hand and then collected data is analyzed for gesture recognition. Data glove is an example of sensor-based gesture recognition. Other sensors used were Wii controller, EMG sensors, accelerometer sensors, etc. Sensor based recognition has certain limitations. First of all, it requires a proper hardware setup which is very expensive. Secondly, it hinders the natural movement of the hand. So, to overcome the limitation of sensor-based recognition vision-based techniques came into existence.Vision based techniques uses one or cameras to capture the hand images. Various type of cameras used for capturing image can be stereo cameras, monocular cameras, fish eye cameras, time- of –flight cameras, infrared cameras, etc.Vision based techniques uses various image processing algorithms to get hand posture and movement of hand. Some vision-based techniques use colored markers to get the position of hand. But the vision-based recognition also has some limitations that it is affected by illumination changes and cluttered backgrounds.Vision based techniques are further divided into two categories – 3D model based and Appearance base recognition. Model based approaches uses 3D hand model to search kinematics parameters by comparing 2D projection of 3D hand image and input frame. 3D model is further divided into volumetric 3D recognition [10] and skeleton 3D recognition. Because of the complexity of 3D model, it is not preferred.

The Hand Model

As mentioned in the above motion constraints of the hand, each of DIP, PIP, and thumb IP joints has only one DOF. It is also assumed that the MCP joint of the middle finger has only one DOF, but the MCP joints of the other fingers have two DOF; namely, MCP bending angles and abduction angles. Figure1describes the hand model and the positions of the sensor modules and generator coils of the data glove.

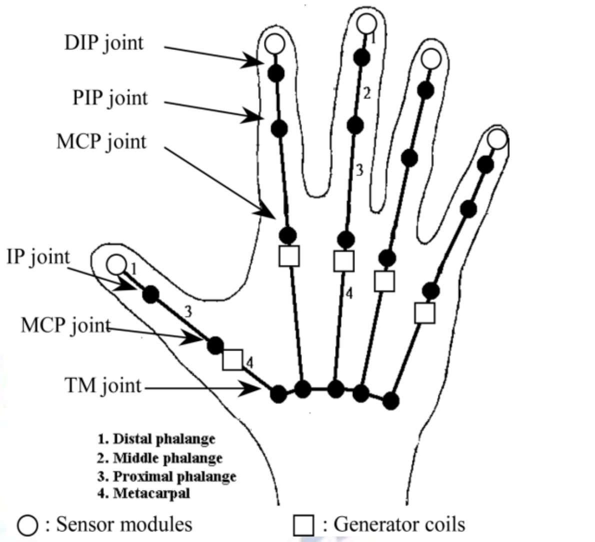


Figure 1: The hand model and the positions of the sensor modules and generator coils

In this data glove, we measure the positions of five fingertips of the hand using five sensor modules and ten generator coils that are arranged into five groups. For the middle finger, one additional sensor coil is installed such that it is co-centered and perpendicular with the generator coils. This sensor coil is used for measuring three abduction angles called index-middle, ring-middle, and pinkie-ring abduction angles. By tracking fingertip positions, the object manipulation tasks in a virtual environment or teleoperation system can be carried out more precisely, because in most of grasping processes, fingertips are the foremost areas that reach the surface of an object. After the fingertip position has been determined, the shape of the associated finger can be modeled using the relationship between adjacent phalanges, and the corresponding bending angles of finger joints can be calculated, too. With this technique, our data glove has the ability of measuring 17 DOF of the hand.

Appearance based techniques are based on extracting features from the visual appearance of the image and compare it with already defined templates. Various features that can be extracted from the image can be shape based featuresthat can be geometric or nongeometric. Geometric features include- position of fingertips, location of palm, centroid, orientation, directionetc. Non- geometric features includes color, silhouette and textures, contour, `edges, image moments, Fourier descriptors, Eigen vectors etc. Some techniques uses skin color modelto extract skin colored pixels. Other techniques HOG features, SIFT features, etc. Appearance based technique is preferred over

model-based technique because of the complexity of the model based techniques.
The basic step of hand gesture recognition is to localize and segment the hand from the image. Various techniques are available for hand segmentation. The most popular and simplest technique is skin color model which is used to get the skin pixels in the image but it has some limitations that skin color of different person can vary and background image can also contain the skin pixels.Other techniques are thresholding which divides the image into two regions foreground and background based on color, depthetc. Some researcher uses background subtractionfor segmenting the hand.

In our approach keeping in view the limitation and simplicity of skin color model we will combine it with thresholding for hand segmentation. Skin color segmentation can be applied on any color space-RGB, HSV, YCbCr, YUV.Every color space has its own benefits. We will use YCbCr color space for skin color segmentation. For gesture recognition HMM, SVM Nearest Neighbor classifier, neural network finite state machine etc.In our approach vision-based hand gesture recognition technique is proposed using a database-driven approach based upon skin color model and thresholding along with an effective template matching using PCA which will use for controlling robotics hand in surgical applications and many other similar applications.The method proposed in their work is independent of the subject and achieved the highest mean accuracy in subject independent test. Oudah et al. gave an analysis of the literature on HGR techniques. Various approaches such as appearance, skeleton, motion, skin color, 3D-model, depth, and deep-learning as a solution to the problem is discussed. But, color-based recognition using glove marker limits the degree of spontaneous and natural interactions.

2. LITERATURE REVIEW

Gesture is a body language which employs actions of the body such as movement of face, hands or any other body part to convey a message. Hand gesture is the most convenient and likely to use among all the visible body actions. An HGR can be regarded as a Human Computer Interaction (HCI) system where the use of hand gestures can be a natural alternative to the traditional modes employing mechanical and electronic devices such as sensors, mouse, joystick, and keyboard [1]. HGR has great importance in many applications such as home appliances control [2], recognition of sign language for disabled people [3], robot control [4] and so on. In the last few decades, many researchers have published solutions for HGR problems related to various applications. Ji et al. explained the use of traditional pattern recognition methods such as Scale Invariant Feature Transform (SIFT) and Histogram of Gradient (HOG) to achieve low-level features [5]. The proposed method is admissible for some fixed datasets because obtaining effective features from a new dataset is a challenging task. Mehr et al. developed a Convolutional Neural Network (CNN) based architecture for recognizing human activity in smart homes using video input [6]. This work has achieved the highest accuracy rate due to the automatic feature extraction from input data. But for any other datasets, the architecture may not be a appropriate model. Mirehi et al. presented a topological approach using graphs for addressing the HGR problem [7]. This work employs Growing Neural Gas(GNG) algorithm to construct the shape features and Linear Discriminant Analysis (LDA) is employed for the purpose of classification. The method proposed in their work is independent of the subject and achieved the highest mean accuracy in subject independent test. Oudah et al. gave an analysis of the literature on HGR techniques [8]. Various approaches such as appearance, skeleton, motion, skin color, 3D-model, depth, and deep-learning as a solution to the problem is discussed. But, color-based recognition using glove marker limits the degree of spontaneous and natural interactions. Sharma et al. put forward a novel model for HGR using canny edge detection, Oriented Fast and Rotated Brief (ORB) and Bag of Word (BoW) technique [9]. ORB feature extraction has been tested against HOG, Principal Component Analysis (PCA) and Local Binary Patterns (LBP) on the same dataset. ORB appears to be a more natural approach as compared to PCA or LBP as it is intuitively based on statistical study of data. ORB presents better results, as the number of features has been reduced in comparison with HOG and PCA. HOG would not give desired results if the object to be detected is a very small part of the image or is entirely covering most of the image.

3.PROPOSED METHODOLOGY

Gesture is a body language which employs actions of the body such as movement of face, hands or any other body part to convey a message. Hand gesture is the most convenient and likely to use among all the visible body actions. An HGR can be regarded as a Human Computer Interaction (HCI) system where the use of hand gestures can be a natural alternative to the traditional modes employing mechanical and electronic devices such as sensors, mouse, joystick, and keyboard.

3.1 Image Acquisition

Images are acquired using the 13-megapixel real-aperture camera in controlled background as well as by varying the lightning conditions.The useful information lies on certain part of an image known as the Region of Interest (ROI). The objective of the segmentation phase is to extract the ROI. Segmentation is achieved through the following steps: 1) Skin Masking: The first stage of hand gesture segmentation is the skin masking process. It is unreliable for classifiers like SVM to have extra data or noise. Inorder to extract the ROI which has only the hand image, we are employing the skin masking technique. All the images in our dataset are in RGB color space. The first step in skin masking technique is to convert the images to HSV space. In order to perform skin masking, we have to set lower and upper boundaries for the HSV images. This step is performed to ensure that all colors other than that of skin is removed from the image. As a result of skin masking, skin area will be represented by light color pixels and non-skin area will be represented by the pixels that are dark in color. After extracting the ROI, the images are converted into grayscale before the next stage of preprocessing. Fig. 3(b) shows the result of performing skin masking on a sample image.The basic step in hand gesture recognition is to segment the hand from the whole image so that it can be utilized for recognition. In our proposed color skin color segmentation is applied to segment the hand. As skin color of different person can vary and background image can also contain the skin pixels so after skin color model Otsu Thresholding is applied to remove the background

3.2 Conversion from RGB to YCbCr

The proposed skin color segmentation in applied to YCbCr color space. So first of all RGB color space is converted to YCbCr color space. Y represents the luminance and Cb and Cr represents chrominance. The RGB color space is converted to YCbCr color space using the following equation:

$$Y = 0.299R + 0.587G + 0.114\,B$$
$$Cb = (B - Y) * 0.564 + 128$$
$$Cr = (R - Y) * 0.713 + 128 \qquad \text{.........(1)}$$

3.3 Skin Color Segmentation

The skin color segmentation is used to classify the pixel as skin pixel or non-skin pixel. As or hand is connected component made of skin pixels we will get the hand after skin color segmentation. Steps for skin color segmentation:

1. The first step in skin color segmentation to specify the range for the skin pixels in YCbCr color space.

$$[R_{Cb}, R_{Cb}'] = [77, 127] \;\; \&$$
$$[R_{Cr}, R_{Cr}'] = [133, 173] \qquad \text{.............(2)}$$

2. Find the pixels (p) that are in the range defined above:is lower and upper bound for Cb component.

$$R_{Cb} \le Pixel\ value(Cb(i,j)) \le R_{Cb}'$$
$$R_{Cr} \le Pixel\ value(Cr(i,j)) \le R_{Cr}' \qquad \text{........(3)}$$

3. Summation of all the pixels in the above step belongs to Region of interest i.e hand.

$$ROI = \sum p(i,j) \qquad \text{..........(4)}$$

After Skin color segmentation we will the hand but may be some other pixels in the background also. To remove that background pixels, we use Otsu Thresholding.

3.4 Otsu Thresholding

Thresholding is used to separate the object from its background by assigning pixel to either background or foreground based on threshold value. In our proposed system hand is in foreground. Otsu threshold is a global thresholding method which chooses threshold that minimizes within class variance.

1. Calculating threshold value: In MATLAB there is a function Gray threshes (I) which calculate global threshold value using Otsu Threshold. TH = gray thresh (I).

2. Convert Image pixel values into binary value according to THR. Then

$$g(i,j) = \begin{Bmatrix} 1 & if\ p(i,j) \geq T \\ 0, & otherwise \end{Bmatrix} \quad \ldots\ldots\ldots..(5)$$

3.5 Gesture Recognition

One of the important techniques of recognition is template matching in which a template to recognize is available and is compared with already stored template. In our approach PCA method for feature extraction and matching is used. Principal Component Analysis: PCA is used to reduce the dimensionality of the image while preserving much of the information. It is the powerful tool for analyzing the data by identifying patterns in the dataset and reduces the dimensions of the dataset such that maximum variance in the original data is visible in reduced data. PCA was invented by Karl Pearson in 1901. It works by converting set of correlated variables to linearly uncorrelated variable called principal components. Principal components are calculated by computing Eigen vectors of covariance matrix obtained from the group of hand images. The highest M eigenvectors contains the maximum variance in the original data. These principal components are orthogonal to each other and the first component is in the direction of greatest variance.

KNN

The K-Nearest Neighbors (KNN) classifier is a valuable tool in the realm of plant leaf disease classification. It operates on the principle that similar data points are likely to share the same class labels. To utilize KNN for this purpose, a dataset of plant leaf images, each associated with a specific disease class, must first be gathered and preprocessed. These images are then transformed into a consistent format through resizing and data augmentation. Following preprocessing, relevant features are extracted from the images, which can encompass color histograms, texture characteristics, The dataset is typically divided into two subsets: a training set for model training and a testing/validation set for performance evaluation. Feature normalization is crucial to ensure that each feature contributes equally to the classification process. The choice of the K parameter, representing the number of nearest neighbors to consider during classification, is a pivotal decision, often determined through techniques like cross-validation.

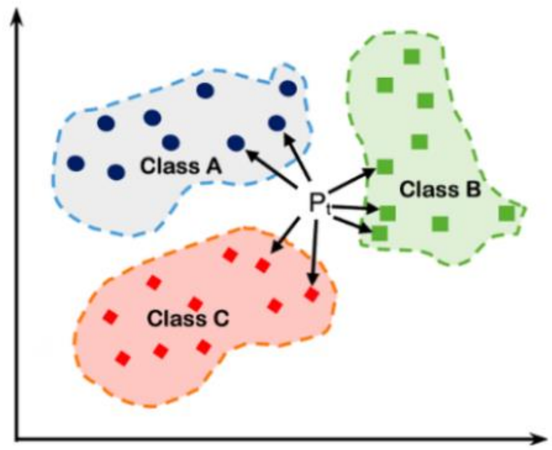


Figure 1: KNN MODEL

Once the K value is selected, the KNN classifier is trained on the training data, effectively memorizing the feature vectors and their corresponding class labels. Classification of a new leaf image involves extracting its features and identifying the K nearest neighbors in the training set using a distance metric, such as Euclidean distance or cosine similarity.A majority voting mechanism is then applied among the K nearest neighbors to assign a class label to the test image. The class that appears most frequently among these neighbors becomes the predicted class.

3.5 SVM

In machinelearning, support vector machines are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

When data are not labeled, supervised learning is not possible, and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups, and then map new data to these formed groups. The clustering algorithm which provides an improvement to the support vector machines is called support vector clustering and is often used in industrial applications either when data is not labeled or when only some data is labeled as a preprocessing for a classification pass More formally, a support vector machine constructs a hyperplane or set of hyper planes in a high- or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization of the classifier.

3.5.1 LINEAR SVM

We are given a training dataset of points of the form where there are either 1 or −1, each indicating the class to which the point belongs. Each is a dimensional real vector. We want to find the "maximum-margin hyper plane" that divides the group of points for which from the group of points for which which is defined so that the distance between the hyperplane and the nearest point from either group is maximized. Any hyperplane can be written as the set of points satisfying

$$\vec{w}\cdot\vec{x}+b=0, \qquad \text{...............(6)}$$

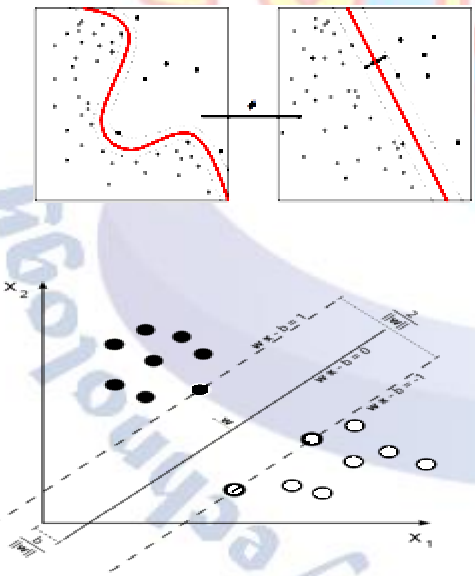


Figure 2: Linear SVM along with graph

Maximum-margin hyperplane and margins for an SVM trained with samples from two classes. Samples on the margin are called the support vectorswhere is the (not necessarily normalized) normal vector to the hyperplane. The parameter determines the offset of the hyperplane from the origin along the normal vectorhyper plane is the hyper plane that lies halfway between them. These hyper planes can be described by the equations. Geometrically, the distance between these two hyper planes is so to maximize the distance between the planes we want to minimize. As we also have to prevent data points from falling into the margin, we add the following constraint: for each either. These constraints state that each data point must lie on the correct side of the margin.

3.5.2 Soft-margin

To extend SVM to cases in which the data are not linearly separable, we introduce the *hinge loss* function, This function is zero if the constraint in (1) is satisfied, in other words, if lies on the correct side of the margin.For data on the wrong side of the margin, the function's value is proportional to the distance from the margin. We then wish to minimize where the parameter determines the tradeoff between increasing the margin-size and ensuring that the ie on the correct side of the margin. Thus, for sufficiently small values of , the soft-margin SVM will behave identically to the hard-margin SVM if the input data are linearly classifiable, but will still learn a viable classification rule if not

3.5.3 Feature Extraction Stage

Feature extraction is the process of getting useful information from the word/character image. The information will be used to generate modules to train the classifier and to be used for classification purposes. In general there are two categories of features extracted, structural and statistical features. Choosing the right feature extraction method might be the most important step for achieving a high recognition rate. However, in some cases the combination of several features extraction types could be a wise decision to enhance the overall recognition performance. Structural features are the character/word image geometrical and topological information. Those obtained information include the number of PAWS, descenders, ascenders, dot below the baseline, above the baseline, etc. Figure shows a structural features example. Statistical feature are numerical measures computed over the images. They include pixel densities, histograms of chain code directions, moments, Fourier descriptors

Training and Recognition

This stage is considered as the primary stage for the system. It depends on the previous stages so that defect in the earlier stages will affects the recognition process and will lead to a low recognition rate. More information about this stage will be covered in the classification's methodology section

Classifier Fusion Model: Hybrid Ensemble Classifier

The predictions of individual classifiers (modified SVM and KNN) were combined to get the result of the classifier fusion model. The proposed classifier fusion model called as the hybrid ensemble classifier is shown in Fig. The individual classifiers were combined using majority voting technique.

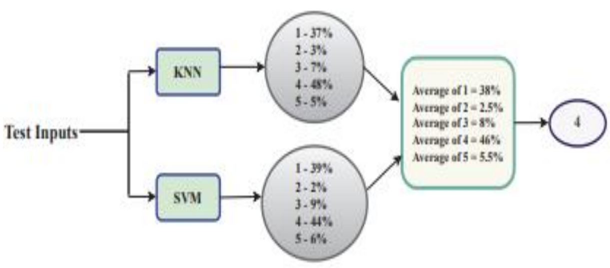


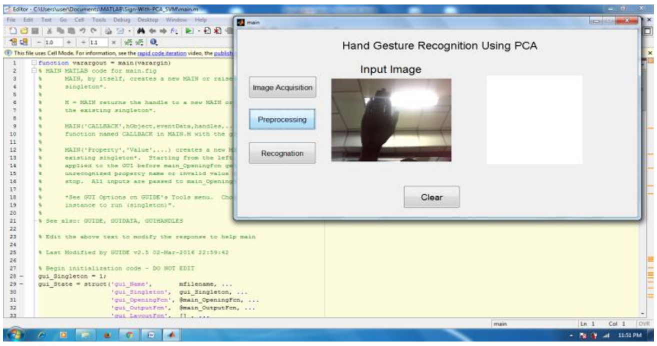
Figure 3: Proposed hybrid ensemble classifier

The modified approach enhances the accuracy of classification and alleviate the class-imbalance issue. gives an overview of the modified SVM approach.

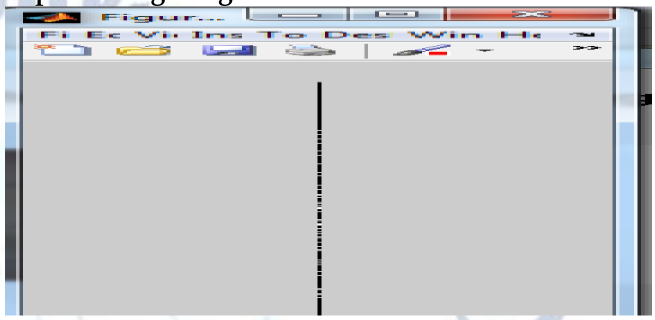
4. RESULTS& DISCUSSION

In this work, we are dealing with the the hand gestures which are recognized by the electronic devices using SVM. Here in my project I have taken 6 types of hand gestures with which I am displaying the numbers accordingly. In this project I have taken the testing data base which contains the pictures of all the 6 different types of gestures which are captured in different directions, From all these gestures one should be matched with the image acquired though the web cam.
The sizes of each gesture that are stored in Test data base are given as follows
A – 97 Images
B – 22 Images
C – 26 Images
D – 21 Images
Five – 134 Images
V – 95 Images
Here in the following figures I am showing the simulation results by taking Five kind of Gestures clearly, where all the remaining kind of Gestures also will have the same kind of results

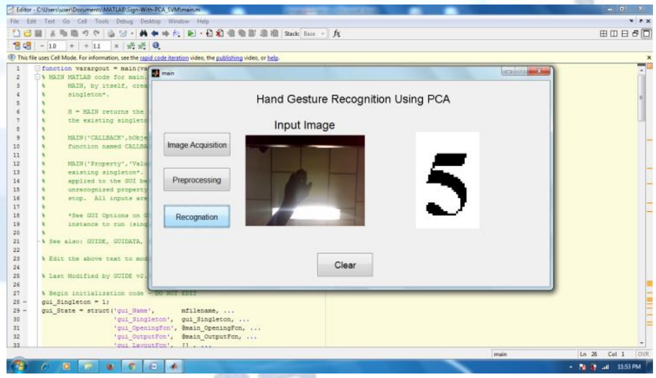
Image acquisition:



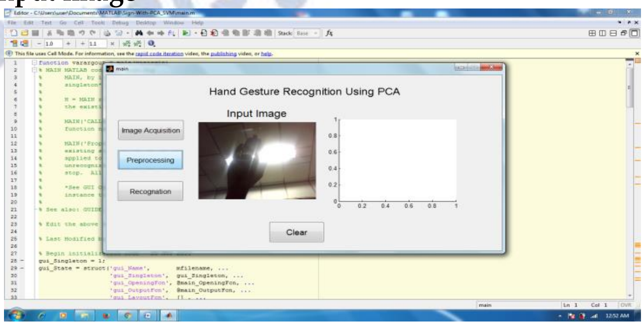
Preprocessing image



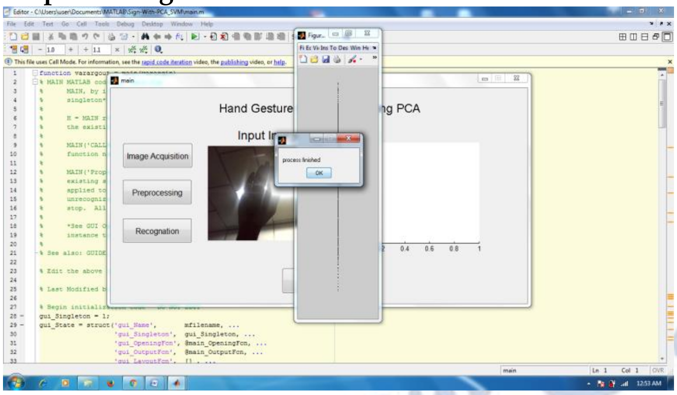
Recognition



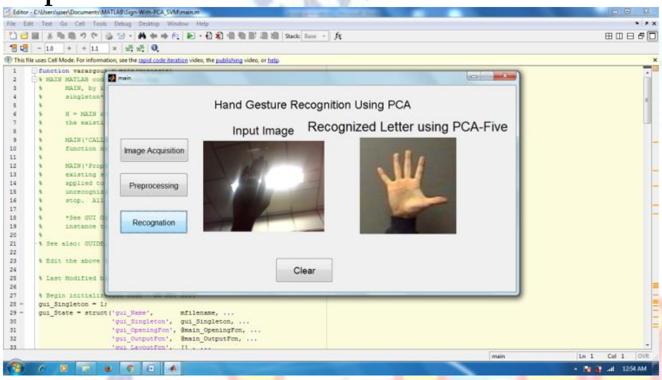
Input image

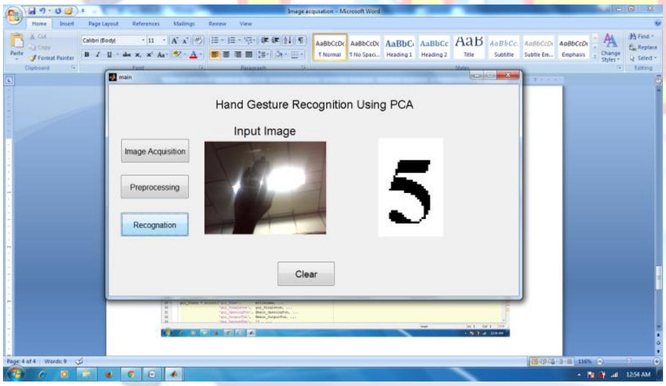


Preprocessing



Output





5.CONCLUSIONS

In this paper the hand gesture recognition system is developed using skin color model, Otsu thresholding and Advanced PCA(SVM). The system is tested in controlled background and indifferent lightning conditions. The database collected in the ideal conditions has proved to be the most efficient database in terms of accuracy and gives 80% accuracy and when the lightning conditions are changed the accuracy decreases as compare to the previous one. The system shows 74.43% with low brightness images.

The hand images have been obtained for the purpose of human computer interactions for the operation theatre robots, which must understand the hand language in order to take the actions. Our research empowers the medical experts to pass the instruction to the robotic hands remotely to add the accuracy in the operations. But the proposed model is not capable of working with the images containing hands of other than skin color. The proposed model does not evaluate the images clicked in other light colors where the hand gestures has been clicked and the model work only with static gesture .In future the system can be upgraded to support dynamic gestures and an application for controlling medical operations can be developed using the system.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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