Hand Gesture Detection and Recognition Using Principal Component Analysis

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Abstract—This paper presents a real time system, which includes detecting and tracking bare hand in cluttered background using skin detection and hand postures contours comparison algorithm after face subtraction, and recognizing hand gestures using Principle Components Analysis (PCA). In the training stage, a set of hand postures images with different scales, rotation and lighting conditions are trained. Then, the most eigenvectors of training images are determined, and the training weights are calculated by projecting each training image onto the most eigenvectors. In the testing stage, for every frame captured from a webcam, the hand gesture is detected using our algorithm, then the small image that contains the detected hand gesture is projected onto the most eigenvectors of training images to form its test weights. Finally, the minimum Euclidean distance is determined between the test weights and the training weights of each training image to recognize the hand gesture.

Keywords-hand gesture; hand posture; PCA.

I. INTRODUCTION

Hand gestures provide a natural and intuitive communication modality for human-computer interaction. Efficient human computer interfaces (HCI) have to be developed to allow computers to visually recognize in real time hand gestures. However, vision-based hand tracking and gesture recognition is a challenging problem due to the complexity of hand gestures, which are rich in diversities due to high degrees of freedom (DOF) involved by the human hand. In order to successfully fulfill their role, the hand gesture HCIs have to meet the requirements in terms of real-time performance, recognition accuracy and robustness against transformations and cluttered background. To meet these requirements, many gesture recognition systems used the help of colored markers or data gloves to make the task easier [1]. However, using of markers and gloves sacrifices the user's convenience. In this paper, we focus on bare hand gesture recognition without help of any markers and gloves.

Detecting and tracking hand gestures in a sequence of images help in extracting hand region. Thus, processing time will be reduced and accuracy will be increased as the features of that region will represent the hand gesture only. Skin color [2, 3, 4] is a significant image feature to detect and track human hands. However, color-based methods face the challenge of removing other objects with similar color such as face and human arm. To solve this problem, we used our technique that used in [5] to detect hand gestures only using face subtraction, skin detection and hand postures contours comparison algorithm. We used Viola-Jones method [6] to detect face and this method is considered the fastest and most accurate learning-based method. The detected face will be subtracted by replacing face area with a black circle. After subtracting the face, we detected the skin area using the hue, saturation, value (HSV) color model since it has real time performance and it is robust against rotations, scaling and lighting conditions. Then, the contours of skin area were compared with all the loaded hand gestures contours to get rid of other skin like objects existing in the image. The hand gesture area only was saved in a small image, which will be projected onto the most eigenvectors of training images to form its test coefficient vector.

PCA has been successfully applied on human face recognition using the concept of "eigenface" [7]. The input image is projected to a new coordinate system consisting of a group of ordered eigenvectors, and the M highest eigenvectors retain the most of the variation presented in the original image set. The goal of PCA is to reduce the dimensionality of the image data to enhance efficiency by expressing the large 1-D vector of pixels constructed from 2-D hand gesture image into the compact principal components of the feature space. This can be called eigenspace projection. Eigenspace is calculated by identifying the eigenvectors of the covariance matrix derived from a set of hand postures training images (vectors). These eigenvectors stand for the principal components of the training images [8] and are frequently ortho-normal to each other.

PCA based approaches normally contain two stages: training and testing. In the training stage, an eigenspace is established from the hand postures training images using PCA and the hand postures training images are mapped to the eigenspace for classification. In the testing stage, a hand gesture test image is projected to the same eigenspace and classified by an appropriate classifier based on Euclidean distance. However, PCA lacks the detection ability. Besides, its performance degrades with scale, orientation and light changes [7].

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In this paper, we used our approach in [5] to detect and track different hand postures and can be recognized using Principal Component Analysis (PCA), which is used to achieve fully real-time performance and accurate classification of hand gestures. With this approach, we can detect, track and recognize a set of bare hand gestures. Since all the training images were used with different scales, rotations and lighting conditions, the system also shows reasonable robustness against scale, rotation, different illuminations and cluttered backgrounds. Therefore, the system can work in different environments.

The major contribution of this paper is that we have achieved real-time performance and accurate recognition for the bare hand postures using our approach in [5] for detecting and tracking hand posture and PCA for recognition.

The paper is organized as follows: section two introduces related work; the third section describes our system in details, the training stage and the testing stage including detection and tracking hand gestures using our approach in [5] and recognition using PCA; section four provides experimental results; the last section gives the conclusion of our method.

II. RELATED WORK

There are mainly two categories for Vision based hand gesture recognition, which are the 3 dimensional (D) hand model based methods and the appearance based methods [9]. Many approaches that used the 3D hand model based technique [10, 11, 12, 13] depend on the 3 D kinematic hand model with considerable *degrees of freedom (*DOF), and calculate the hand parameters by comparison between the input frames and the 2 D appearance projected by the 3D hand model. This will be suitable for realistic interactions in virtual environments. The 3D hand model based technique provides a rich description that permits a wide class of hand gestures. However, since the 3D hand models are articulated deformable objects with many DOF's, a huge image database is required to deal with the entire characteristic shapes under several views. Another drawback is the difficulty of feature extraction and inability to handle singularities that occur from unclear views.

Appearance based techniques extract image features to model the visual appearance of the hand and compare these features with the extracted features from the video frames. They have real time performance because of the easier 2 D image features that are used. A simple method, searching for skin colored regions in the image, was used in [14]. However, this method has some shortcomings; first, it is very sensitive to lighting conditions. Secondly, it is required that no other skin like objects exist in the image.

In [15], scale-space color features are used to recognize hand gestures, which are based on feature detection and user independence. However, the system shows real time performance only when no other skin colored objects exist in the image.

The authors of [16] obtained a clear-cut and integrated hand contour to recognize hand gestures, and then computed the curvature of each point on the contour. Due to noise and unstable illumination in the cluttered background, the segmentation of integrated hand contour had some difficulty.

There have been a number of research efforts recently on local invariant features [17, 18, 19]. In [17], Adaboost learning algorithm and Scale Invariance Feature Transform (SIFT) features were used to achieve in-plane rotation invariant hand detection. In addition, a sharing feature concept was used to speed up the testing process and increase the recognition accuracy. Therefore, efficiency of 97.8% was achieved. However, several features such as a contrast context histogram had to be used to achieve hand gesture recognition in real time. In [18, 19], Haar like features were applied for hand detection. Haar like features concentrate more on the information within a certain area of the image rather than each single pixel. To enhance classification accuracy and attain real time performance, the AdaBoost learning algorithm, which can adaptively choose the best features in each step and combine them into a strong classifier, can be used.

With the learning-based object detection technique proposed by Viola and Jones [6], the bare hand detection without any restriction on the background evolves dramatically [20]. The detection method attains robust detection, but needs a large training time for obtaining the cascaded classifier. Besides, hand detection with the Viola-Jones detector can be done with about 15 degree in-plane rotations compared to 30 degree on face [21]. Even though rotation invariant hand detection can be achieved using the same Adaboost framework in a way of treating the problem as a multi-class classification problem, the training process requires much more training images and more computational power for both training and testing.

Keypoint features extracted from SIFT algorithm can be used in their raw format for direct image matching [22], or vector-quantized keypoints features into a representation like the bag-of-words representation of text documents. There were a lot of researches using this vector-quantized, or bag-of-features representation, for image classification [22, 23, 24].

Recently, bag-of-features representations have shown outstanding performance for action and gesture recognition [25, 26, 27]. They permit to recognize a rich set of actions ranging from simple periodic motion (waving, running) to interactions (kissing, shaking hands) [28, 29, 30, 31]. However, "bag-of-features" approaches exclusively rely on the dense local motion features. They do not have the relations between the features in the spatial and the temporal domains. These are significant correlation, which are useful for recognition. There were a lot of researches on expanding "bag-of- features" to include the spatial relation in the context of object categorization [23, 32, 33, 34, 35]. According to our approach in [5], we used bag-of-features and multiclass support vector machine (SVM) techniques to recognize different hand gestures, which have real time performance with accuracy of 96.23%.

III. SYSTEM OVERVIEW

Our hand gesture recognition system consists of two stages: the offline training stage, which is shown in Figure 1 and the online testing stage, which is shown in Figure 3. The xml file that contains the mapping of every training image to the eigenspace will be built in the training stage and will be loaded and used in the testing stage to recognize hand gestures captured from a webcam.

A. Training Stage

The training stage is shown in Figure 1. PCA decreases the dimensionality of the training images set, leaving only those features that are important for hand gesture recognition. It reduces each N x N training image into a vector of length N^2 x 1. The average hand gesture vector Y is computed by adding all the training images and then dividing the result by the number of all the training images. Each training image is normalized by subtracting it from the mean Y. The main idea of the PCA is based on the eigenvectors of the covariance matrix of the set of hand posture training images. These eigenvectors can by thought as a set of features which characterize the variation between hand posture training images. Hand posture training images are projected into the subspace spanned by a hand posture space. The hand posture space is defined by the eigenspaces which are the eigenvectors of the set of hand postures. Each training image corresponds to each eigenvector. An eigenvector can be displayed as an eigenspace. Then in the testing stage, for every hand gesture detected is classified by comparing its position in hand gesture space with the positions of every hand posture training images. Each hand posture image in the training set is represented a linear combination of the eigenspaces which indicate a feature space that spans the variations among the known hand posture training images. The number of eigenspaces is equal to the number of hand posture images in the training set. The hand postures can also be approximated using only the best eigenspaces which have the largest eigen values.

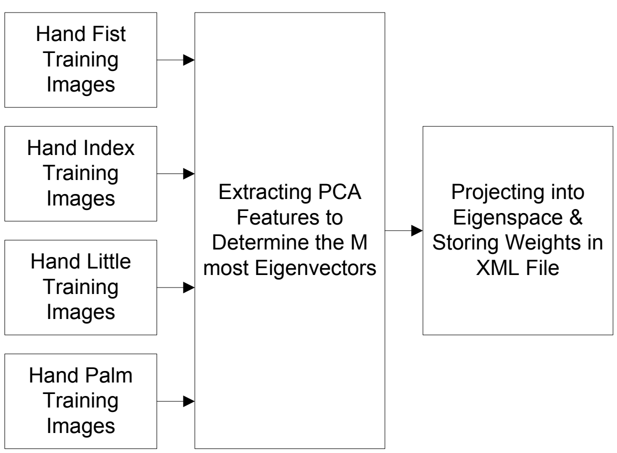


Figure 1. Training stage.

Since PCA performance decreases with scale, orientation and light changes [7], we used 40 training images with size of 160×120 pixels for each hand posture: fist, index, little and palm as shown in Figure 2 with different scales, rotations and lighting conditions to make PCA invariant against these changes. Eigenvectors and eigenvalues are computed on the covariance matrix of the training images for all hand postures. The M highest eigenvectors are kept. Finally, the hand posture training images are projected or mapped into the eigenspace, and their weights are stored in xml file which will be loaded and used in the testing stage. The weights of every training image are simply the dot product of each normalized training image with the M eigenvectors.

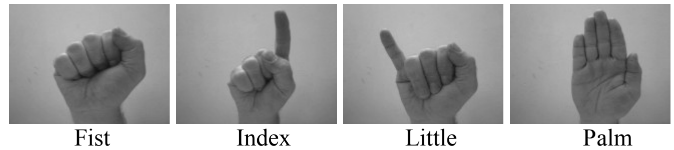


Figure 2. Hand postures used in training stage.

B. Testing Stage

The testing stage is shown in Figure 3. Before capturing frames, we loaded the xml file, which contains the M highest eigenvectors and weights of training images. After capturing frames from webcam or video file, we detected the face and subtracted it before using a skin detection and hand postures contours comparison algorithm because the skin detection will detect the face and the face's contours very close to the fist hand posture contours. To get rid of other skin like objects existing in the image, we make sure that the contours of the detected skin area comply with the contours of any hand postures contours to detect and save the hand gesture only in a small image (160×120 pixels). Then, the small image that contains the hand gesture only is classified by comparing its position in hand gesture space with the positions of known hand posture training images using xml file that built in the training stage.

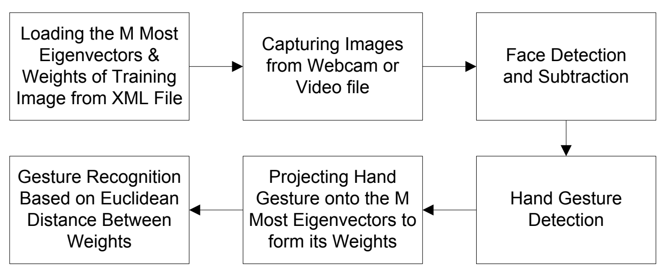


Figure 3. Testing stage.

1. Face Detection and Subtraction

We used the skin detection and contours comparison algorithm to detect the hand gesture and this algorithm can also detect the face because the face has a skin color and its contours like the hand fist posture contours. To get rid of face area, we detected the face using Viola and Jones method [6] and then subtracted the face before applying the skin detection algorithm to detect the hand gesture only by replacing face area with a black circle for every frame captured. The Viola and Jones algorithm has a real time performance and achieving accuracy as the best published results [6].

First, we loaded a statistical model, which is the XML file classifier for frontal faces provided by OpenCV to detect the faces from the frames captured from a webcam during the testing stage. Once the face had been detected by the XML file classifier for every frame captured, we replaced the detected face area with a black circle to remove the face from the skin area. In this way, we make sure that the skin detection will be for hand gesture only as shown in Figure 4.

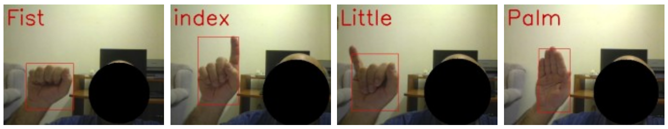


Figure 4. Face detection and subtraction.

2. *Hand Gesture Detection*

Detecting and tracking human hand in a cluttered background will enhance the performance of hand gesture recognition using PCA in terms accuracy and speed because the hand gesture space extracted will represent the hand gesture only. Besides, we will not be confined with the frame resolution size captured from a webcam or video file, because we will always extract the PCA features of the small image (160×120 pixels) that contains the detected hand gesture area only not the complete frame. In this way the speed and accuracy of recognition will be the same for any frame size captured from a webcam such as 640×480, 320×240 or 160×120 and the system will be also robust against cluttered background because we process the detected hand gesture area only. The small image size (160×120 pixels) that contains the detected hand gesture area only in the testing stage has to be complied with the training images size of training stage.

For detecting hand gesture using skin detection, there are different methods including skin color based methods. In our case, after detecting and subtracting the face, skin detection and contours comparison algorithm was used to search for the human hands and discard other skin colored objects for every frame captured from a webcam or video file. Before capturing the frames from a webcam, we loaded four templates of hand postures as shown in Figure 5: fist, index, little and palm to extract their contours and saved them for comparison with the contours of skin detected area of every frame captured. After detecting skin area for every frame captured, we used contours comparison of that area with the loaded hand postures contours to get rid of other skin like objects exist in the image. If the contours comparison of skin detected area complies with any one of the stored hand postures contours, a small image (160×120 pixels) will enclose the hand gesture area only and that small image will be used for extracting the PCA features.

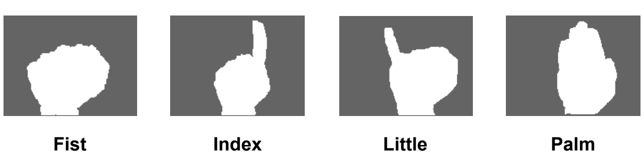


Figure 5. Templates of hand postures.

In our implementation we used the *hue, saturation, value* (HSV) color model for skin detection since it has shown to be one of the most adapted to skin-color detection [36]. It is also compatible with the human color perception. Besides, it has real time performance and robust against rotations, scaling and lighting conditions and can tolerate occlusion well.

From a classification approach, skin-color detection can be considered as a two class problem: skin-pixel vs non-skin-pixel classification. There are many classification techniques such as thresholding, gaussian classifier, and multilayer perceptron [37]. In our implementation we used the thresholding method, which has the least time on computation compared with other techniques and this is required for real time application. The basis of thresholding classification is to find the range of two components H and S in HSV model as we discarded the Value (V) component. Usually a pixel can be viewed as being a skin-pixel when the following threshold ranges are simultaneous satisfied: $0° < H < 20°$ and $75 < S < 190$.

Once the skin area had been detected, we found contours of the detected area and then compared them with the contours of the hand postures templates. If the contours of the skin area comply with any of the contours of the hand postures templates, then that area will be the region of interest by enclosing the detected hand gesture with a rectangle, which will be used in tracking the hand movements and saving hand gesture in a small image (160×120 pixels) for every frame captured. The small image will be used in extracting the PCA features.

3. *Hand Gesture Recognition*

As we mentioned before, the xml file that contains the weights of hand posture training images in the eigenspace was loaded before capturing frames from a webcam and will be used in recognition. The small image (160×120 pixels) that contains the detected hand gesture only for every frame captured was converted into a PGM format and was projected onto the M most eigenvectors to form its weights (coefficient vector) using the xml file that contains the M most eigenvectors and weights of every hand posture training image in the eigenspace. Finally, the minimum Euclidean distance between the detected hand gesture weights (coefficient vector) and the training weights (coefficient vector) of each training image is determined to recognize the hand gesture.

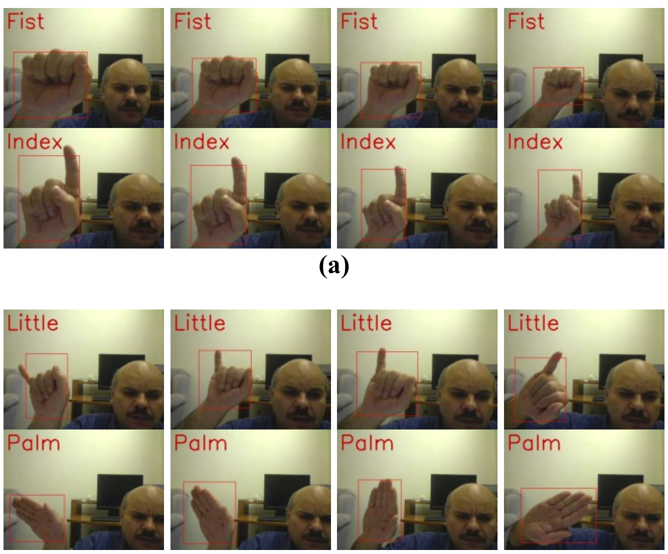
IV. EXPERIMENTAL RESULTS

We tested four hand gestures: the fist gesture, the index gesture, the little finger gesture and the palm gesture. The camera used for recording video files in our experiment is a low-cost Logitech QuickCam web-camera that provides video capture with the resolution of 320×240, 15 frames-per second using Pentium 4 CPU 3.2 GHz Computer. This frame rate matches the real time speed.

Ten video files with the resolution of 640×480 had been recorded for each hand gesture: fist, index, little finger and palm using a commercial grade webcam. The length of each video file was 100 images. The hand gestures were recorded with different scales, rotations and illuminations conditions and with a cluttered background. The test was run for the forty video files to evaluate the performance of the PCA classifier model for each gesture. The trained PCA classifier shows a certain degree of robustness against scale, rotation, illumination and cluttered background. Table 1 shows the performance of the PCA classifier for each gesture with testing against scale, rotation, illumination and cluttered background. The recognition time did not increase with cluttered background or increasing the resolution of video file because the PCA features will be extracted from the small image (160×120 pixels) that contains the detected hand gesture only. We repeated the experiment with other ten video files for each hand gesture with the resolution of 320×240 pixels, the same time was needed to recognize every frame with the same accuracy as 640×480 videos results because the PCA features were extracted in both cases from the small image that contains the hand gesture only. Figure 6 shows some correct samples for hand gesture recognition using PCA classifier for fist, index, little and palm gestures with testing against scale, rotation, illumination and cluttered background.

TABLE I. THE PERFORMANCE OF THE PCA CLASSIFIER WITH CLUTTERED BACKGROUND (640×480 PIXELS).

Gesture Name	Number of frames	Correct	Incorrect	Recognition Time (Second/frame)
Fist	1000	933	67	0.055
Index	1000	928	72	0.055
Little	1000	912	88	0.055
Palm	1000	945	55	0.055



(a)

(b)

Figure 6. Hand gesture detection and recognition with cluttered background against: (a) scale. (b) rotation.

V. CONCLUSION

In this paper, we have proposed a real-time system that consists of two modules: hand detection and tracking using face subtraction, skin detection and contours comparison algorithm and gesture recognition using Principle Components Analysis (PCA). The PCA is divided into two stages: training stage where hand postures training images are processed to calculate the M highest eigenvectors and weights for every training image, and testing stage where the weights of the detected hand gesture captured from a webcam is matched with training images weights to recognize hand gesture. The testing stage proves the effectiveness of the proposed scheme in terms of accuracy and speed as the coefficient vector represents the detected hand gesture only. Experiments show that the system can achieve satisfactory real-time performance regardless of the frame resolution size as well as high classification accuracy above 90% under variable scale, orientation and illumination conditions and cluttered background.

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