Static Hand Gesture Recognition using Mixture of Features and SVM Classifier

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***Abstract*—A hand gesture recognition system has a wide area of application in human computer interaction (HCI) and sign language. This work proposes a vision-based system for recognition of static hand gesture. It deals with images of bare hands, and allows to recognize gesture in illumination, rotation, position and size variation of gesture images. The proposed system consists of three phases: preprocessing, feature extraction and classification. The preprocessing phase involves image enhancement, segmentation, rotation and filtering process. To obtain a rotation invariant gesture image, a novel technique is proposed in this paper by coinciding the 1^{st} principal component of the segmented hand gestures with vertical axes. In feature extraction phase, this work extracts localized contour sequences (LCS) and block based features and proposes a novel mixture of features (or combined features) for better representation of static hand gesture. The combined features are applied as input to multiclass support vector machine (SVM) classifier to recognize static hand gesture. The proposed system is implemented and tested on three different hand alphabet databases. The experimental results show that the proposed system able to recognize static gesture with a recognition sensitivity of 99.50%, 93.58% and 98.33% for database I, database II and database III respectively which are better compared to earlier reported methods.**

***Keywords*-American sign language (ASL) hand alphabet; combined features; localized contour sequences (LCS); principal component; static hand gesture; support vector machine (SVM);**

I. Introduction

In today's technical world, the intellectual computing of a proficient human-computer interaction (HCI) or human alternative and augmentative communication (HAAC) is essential in our daily lives. Hand gesture recognition is one of the most important techniques to develop gesture based interface system for HCI or HAAC application [1], [2]. Gestures are communicative, meaningful body motions connecting physical actions of the fingers, hands, arms, face, head, or body with the intent of conveying meaningful information or interacting with the environment [3]. In general, gestures can be classified into static gestures [2], [4]–[6] and dynamic gestures [7], [8]. Static gesture is described in the forms of definite hand configuration or poses, while dynamic gesture is a moving gesture, articulated as a sequence of hand movements and arrangement. However, static gestures communicate certain meanings or some time act as explicit transitions state in dynamic gestures.The sensing techniques which are used in static hand gesture recognition systems include vision-based techniques [2], [5]–[8] and glove-based techniques [9], [10]. In glove-based technique, sensors are utilized to measure the joint angles, the positions of the fingers and the position of the hand in real-time [10]. However, gloves are quite expensive as well as the weights of the glove and the cables of the associated measuring equipment hamper free movement of the hand. Therefore, user interface with recognition system is complicated and less natural for glove-based techniques. However vision-based techniques uses one or more cameras to capture the gesture images, performed by user.

Various features have been reported in the literature [1], [2], [4]–[6], [11] to represent static hand gesture including features like statistical moments [2], [6], block based feature [5], Fourier discriminator (FD) [4], discrete cosine transform (DCT) based feature [11], localized contour sequence (LCS) [1]. However, some benefits [1] of LCS feature that distinguish it from other features are as follows: (i) The LCS is independence of shape complexity. (ii) The LCS can also be used to efficiently characterize partial contours.(iii) The LCS representation is autonomous from derivative computations and it is quite good with respect to contour noise. (iv) Increasing window size tends to increase the magnitude of the LCS. A large number of literatures [1], [2], [4], [5] are reported by the researchers for recognition of static hand gestures. However, accurate features representation and classification of static gestures are still being a challenge for static hand gesture recognition system in real time application.

This paper proposes a vision-based automatic static hand gesture recognition system which consists of preprocessing, feature extraction, classification phase. The preprocessing phase involves following sub-phases: image enhancement which enhances the image using homomorphic filtering and gray world algorithm to overcome illumination variation of grayscale and color image respectively; segmentation which segments hand region from its background image and transforms into binary silhouette; rotation that rotates segmented gesture to make it rotation invariant; filtering that effectively removes background noise and object noise from binary image and smoothen it's contour by morphological filtering technique. This work proposes a rotation invariant technique by coinciding the 1^{st} principal component of the segmented hand gestures with vertical axes to make it rotation invariant. This work proposes a mixture of features (or combined features) by appending LCS features with block based features to represents static hand gesture. The advantage of this combined features is it contain the contour as well as regional information of the gesture. Finally, support vector machine (SVM) classifier is used to recognize gestures class based on their corresponding combined features. The goal of SVM classifier is to project the input data into higher dimensional space where the different classes become linearly separable to reconstruct an optimal separating hyperplane. SVM works on the basis of structural risk minimization principle and it uses empirical risk minimization method to provide better generalization ability than other traditional classification technique. The experiments are conducted on three different hand alphabet databases. Experimental results show that utility of the proposed combined features representation to represent a static hand gesture is better compared to LCS and block based features. The experimental results also indicate that the overall static hand gesture recognition performance of the proposed system is better compared to earlier reported methods.

The rest of the paper is organized as follows: Section II provides detail information of gesture database; Section III explains proposed static hand gesture recognition system in detail; results and discussion are described in Section IV and finally the conclusion is given in Section V.

II. Gesture database

Gesture images from three gesture database are used in this study, which includes grayscale images (database I and database II) and color images (database III). Database I is a repository database of Danish/international hand alphabet which is publically available [12]. It consists of 1000 grayscale images of 25 gesture, 40 sample for each class with spatial resolution (256×248). Database II and database III are indigenously developed using VGA Logitech Webcam (C120) with 24 American Sign Language (ASL) hand alphabet. The databases are constructed by capturing ASL gesture images from 10 volunteers, most of which are not familiar with gesture recognition and each volunteer provides a guide of postures as appear in the ASL browser developed by Michigan State University and BGU-ASL DB [5]. Database II consists of 2400 hand alphabet grayscale images with spatial resolution (320×240). Each ASL hand alphabet contains 100 images with 10 samples per volunteer. The ASL hand alphabets are performed by every volunteer based on different angle, position and distance from camera with different lighting condition. A uniform black background is placed to cover all of workspace. Database III also contains 2400 ASL hand alphabet color images with spatial resolution (320×240). Each ASL hand alphabet comprises of 100 images; 10 samples are performed by every volunteer on non uniform background with variations of angle, position and size changes in different lighting condition.

III. Proposed static hand gesture recognition system

The objective of the proposed system is to recognize static gestures of sing language hand alphabets. The proposed system consists of following three phase: preprocessing, feature extraction and classification.

A. Preprocessing

Preprocessing phase of the proposed system comprises different operations: image enhancement, segmentation, rotation and morphological filter.

1) Image enhancement: For grayscale images of database I and database II, this work uses homomorphic filtering [13] technique to enhance hand gesture image by normalizing illumination variation within it. For color images of database III, this work utilizes gray world algorithm [14] to enhance gesture image by compensating the variation of light. The compensation is done by equalizing the mean of red (R), green (G) and blue (B) channels. Fig. 1 (b) and Fig. 2 (b) represents the results of image enhancement done by homomorphic filtering and gray world algorithm respectively.

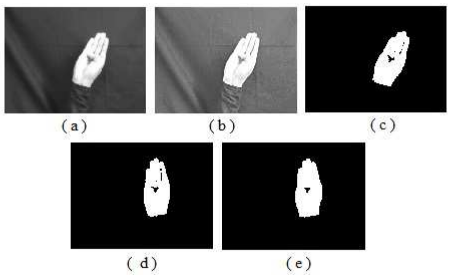

Figure 1. Results of preprocessing step for a grayscale image of database II: (a) Original gesture image; (b) Enhanced image; (c) Otsu segmented image; (d) Rotated image; (e) Morphological filtered image.

2) Image Segmentation: The objective of segmentation is to extract the hand region from the background of the gesture image. For grayscale image of database I and database II, the hand region of the enhanced gesture image is segmented with Otsu segmentation algorithm [15]. The result of Otsu segmentation algorithm of Fig. 1 (b) is shown in Fig. 1 (c).

For color image of database III, the hand is segmented from background of the enhanced gesture image using skin color detection method in YCbCr color space [16]. In contrast to RGB, the YCbCr color space gives better performance under varying lighting condition for it luma-independent characteristic. In this work, a pixel is considered

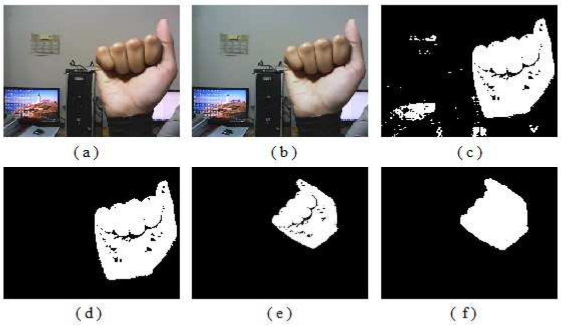

Figure 2. Results of preprocessing step for a color image of database III: (a) Original gesture image; (b) Enhanced image; (c) Detected skin color region; (d) Final segmented image; (e) Rotated image; (f) Morphological filtered image.

as skin pixel if $Th < Y < 255$, $85 < Cb < 128$ and $129 < Cr < 185$, where Th is $(1/3)$ of average Y value of all pixel. The skin color detection result for hand gesture image is shown in Fig. 2 (c). From the detection result it is observed that segmented image also contains other skin color objects not belonging to hand region. Therefore, considering hand region is the largest connected object, other objects are filtered out by comparing their area. The final segmented output of Fig. 2 (b) is shown in Fig. 2 (d).

3) Image Rotation: In this work, an image rotation technique is proposed to make gesture rotation invariant using the direction of 1^{st} principal component of segmented hand gesture image. Stepwise description of the proposed technique is as follows.

1) First, find the direction of 1^{st} principal axes of segmented hand gesture.
2) Find the rotation angle between the 1^{st} principal axes of the segmented hand gesture and vertical axes.
3) Rotate the segmented hand gesture, so that 1^{st} principal axes of the segmented hand gesture coincide with vertical axes.

The results of proposed image rotation technique are shown in Fig. 1 (d) and Fig. 2 (e).

4) Morphological filtering: A morphological filtering technique is applied here to reduce object noise from binary image and to obtain a well defined smooth, closed, and complete segmented hand gesture [12]. This is done using a sequence of dilation and erosion operations over the rotation invariant segmented images. The outputs of morphological filtering are shown in Fig. 1 (e) and 2 (f).

B. Feature Extraction

A feature is a distinctive or characteristic measurement, transform, structural component extracted from a pattern. Feature extraction is a technique that found a feature or a feature set from a pattern with the goal of minimizing the loss of important information.

1) Localized contour sequence: The Localized contour sequence (LCS) which efficiently represents the object's contour [1] is selected as a feature set to represent hand gesture. A well established canny edge detection algorithm [17] is used to detect the edge of the preprocessed hand gesture. A contour tracking algorithm [12] is used to track the contour of the edge detected gesture in the clockwise direction starting from the topmost left contour pixel. If $h_i = (x_i, y_i)$, $i = 1, 2 \ldots, N$ is the i^{th} contour pixel in the sequence of N ordered contour pixels of a gesture. The i^{th} sample $h(i)$ of the LCS for a window of size $w1$ is obtained by computing (1).

$$h\left(i\right) = \left|u_i/v_i\right|, \tag{1}$$

where

$$\begin{aligned} u_i = x_i&[y_{i-(w1-1)/2} - y_{i+(w1-1)/2}] \\ &+y_i[x_{i+(w1-1)/2} - x_{i-(w1-1)/2}] \\ &+ [y_{i+(w1-1)/2}][x_{i-(w1-1)/2}] \\ &-[y_{i-(w1-1)/2}][x_{i+(w1-1)/2}], \end{aligned}$$

and

$$\begin{aligned} v_i = &[(y_{i-(w1-1)/2} - y_{i+(w1-1)/2})^2 \\ &+(x_{i-(w1-1)/2} - x_{i+(w1-1)/2})^2]^{1/2}. \end{aligned}$$

The duration and amplitude of the LCS are varied from gesture to gesture. Therefore, these are normalized by setting its duration as the average LCS duration of training dataset and standard deviation as unity. In this work, the LCS durations are normalized as 150, 300 and 400 for database I, database II and database III respectively. Note that normalized LCS feature set is position and size invariant of gesture images. The detected edge and corresponding normalized LCS of a static hand gesture is shown in Fig. 3.

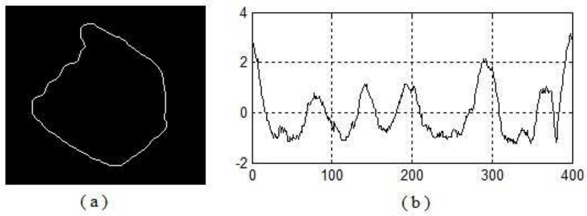

Figure 3. Results of detected edge and corresponding normalized LCS features. (a) Detected edge of a preprocessed gesture image (b) Normalized LCS features for corresponding image.

2) Block based features: A bounding box is constructed around hand region of the preprocessed gesture image. The box is then cropped and partitioned into blocks. A block based feature vector of the image incorporates the aspect ratio of the cropped bounding box, and the average intensity of each block [5]. The block based feature vector of length $V = 1 + B_r \times B_c$, denoted as $f_b = (f_1, \ldots, f_i, \ldots, f_V)$, where B_r and B_c are the number of rows and columns of the block partition. The first feature of f_b represents the aspect ratio of the bounding box, and the remaining features represent block averages indexed row-wise from left to right. The bounding box and a restriction on the height of the static gesture make the block based feature vector position and size invariant. The parameters, B_r and B_c are chosen through heuristic approach [5]. In this work, the gestures of database I and database II are represented by the block based feature vectors of length 13 i.e.$(1 + 4 \times 3)$ and the gestures of database III are represented by the block based feature vectors of length 21 i.e.$(1 + 5 \times 4)$. Fig. 4 shows the artwork of block based feature extraction scheme for a gesture image.

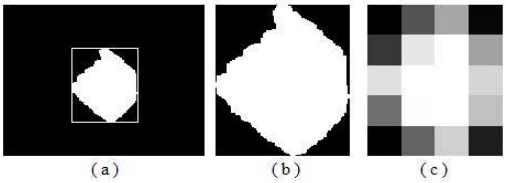

Figure 4. Artwork of block based feature extraction: (a) hand gesture within bounding box, (b) cropped bounding box region and (c) 5×4 block partition.

3) Mixture of features: This work proposes a mixture of features (or combined features) to represent static hand gesture. The combined features are obtained by appending the LCS features with the block based features. The combined features carry contour as well as regional information of the gesture and it incorporates all the advantages of LCS and block based features. Therefore, the combined features provides better representation of the static hand gesture as compared to each of the individual feature set.

C. Classification

In this work, one-against-all (OAA) multiclass SVM classifier [18] is used to classify static hand gestures using combined features. OAA approach constructs K binary SVM models for an K-class problem. The i^{th} SVM is trained with all of the patterns in i^{th} class with positive labels and all other patterns with negative labels. Let, a training set of N data points $\{(u_i, d_i)\}_{i=1}^{N}$ are given, where $u_i \in R^n$ is the pattern to be classified and $d_i \in \{1, ..., K\}$ is class of u_i. The i^{th} SVM solves the following problem that given the i^{th} decision function $f_i(u) = (w^i)^T \phi(u) + b^i$:

$$\begin{aligned} &\min_{w^i,\xi^i,b^i} \;\; P_1(w,\xi) = \tfrac{1}{2}(w^i)^T w^i + C \sum_{j=1}^{N} {\xi_j}^i \\ &subject\,to\; (w^i)^T\phi(u_j) + b^i \geq 1 - \xi_j^i \;\;, \quad if\, d_j = i \\ &\qquad\qquad (w^i)^T\phi(u_j) + b^i \leq -1 + \xi_j^i \;\;, \quad if\, d_j \neq i \\ &\qquad\qquad \xi_j^i \geq 0, \quad j = 1, ..., N \end{aligned} \tag{2}$$

where the training data u_i are mapped to a higher dimensional space by the function ϕ and C is the reguligetion parameter. At testing phase, the class of input pattern u is determined by the largest value of decision functions as represented in (3).

$$class\ of\ u \;\equiv \arg \max_{i=1,....,K} \left((w^i)^T\phi(u) + b^i\right) \tag{3}$$

IV. EXPERIMENT RESULTS AND DISCUSSION

The proposed gesture recognition system is tested on three hand gesture databases. The details of database I, database II and database III are given in Section III. The performance of the proposed system is evaluated on the basis of four statistical indices [19] including classification accuracy (Acc), sensitivity (Sen), positive predictivity (Ppr) and specificity (Spe). These parameters are defined as follows [19]: $Acc = (TP + TN)/(TP + TN + FP + FN)$; $Sen = TP/(TP + FN)$; $Ppr = TP/(TP + FP)$; and $Spe = TN/(TN + FP)$, where TP, TN, FP and FN are true positives, true negatives, false positives and false negative respectively.

To evaluate usefulness of proposed mixture of features (or combined features) for static hand gesture recognition, the experiments are separately conducted on three hand gesture databases with block based, LCS and combined features using multiclass SVM classifier. For these experiments, initially gesture images of each database are divided into two equal part where one part is used to train the SVM classifier and other part is used to test the system performance. The Experimental results are tabulated in Table I. Experimental results indicate that average accuracy, sensitivity, positive predictivity and specificity of the recognition system with proposed features (or combined features) are 99.97%, 99.60%, 99.62% and 99.98% respectively for database I, 99.51%, 94.08%, 94.16% and 99.74% respectively for database II and 99.90%, 98.75%, 98.80% and 99.95% respectively for database III. For more accurate analysis, the performance of the proposed gesture recognition system using block based, LCS and proposed combined features are visualized in forms of receiver operating characteristic (ROC) graph [20]. On an ROC graph, false positive rate (Fpr) and true positive rate (or sensitivity) are separately plotted on the X and Y axis. The false positive rate is defined as $Fpr = FP/(TN + FP)$. In ROC graph, one point in ROC space is better than other if it is located to the more upper left corner. Fig. 5 shows ROC graph of the proposed recognition system with block based, LCS

Table I
RECOGNITION PERFORMANCES OF THE SYSTEM WITH LCS, BLOCK BASED FEATURES AND PROPOSED COMBINED FEATURES.

Data base	Feature	Acc (%)	Sen (%)	Ppr (%)	Spe (%)
Data base I	Block based	99.89	98.60	98.82	99.94
	LCS	99.95	99.40	99.43	99.98
	Proposed	**99.97**	**99.60**	**99.62**	**99.98**
Data base II	Block based	99.11	89.33	89.46	99.54
	LCS	99.47	93.58	93.64	99.72
	Proposed	**99.51**	**94.08**	**94.16**	**99.74**
Data base III	Block based	99.74	96.92	96.99	99.87
	LCS	99.87	98.42	98.47	99.93
	Proposed	**99.90**	**98.75**	**98.80**	**99.95**

and proposed combined features for three district database. From Table I and Fig. 5, it is seen that proposed combined features representation offers better recognition performance compared to block based and LCS features.

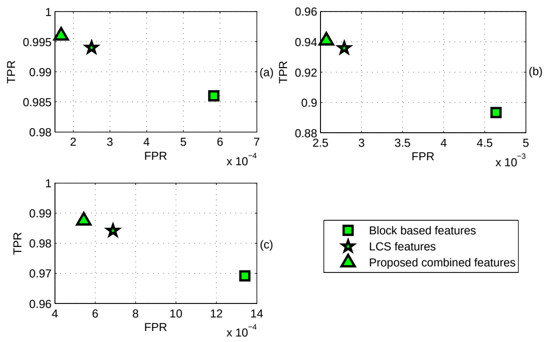

Figure 5. ROC graphs of proposed recognition system with block based, LCS and proposed combined features for (a) database I, (b) database II and (c) database III.

To investigate overall performance of the proposed recognition system and to compare the recognition performance with few recently reported state-of-art methods like HU-ANN (Hu invariant moments feature with artificial neural network classifier) [2], DCT-KNN (DCT coefficient feature with k-nearest neighbor classifier) [11] and Krawtchouk-MD (Krawtchouk moments feature with minimum distance classifier) [6], the experiments are separately conducted on three distinct database. In this study, performance is evaluated via a 2-fold cross validation test. The advantages of cross validation are that test sets are independent and reliability of the performance is improved. Experimental results of the cross validation test are tabulated in Table II. From Table II,

Table II
THE CROSS VALIDATION TEST RESULTS OF THREE RECENTLY REPORTED METHODS AND PROPOSED SYSTEM.

Data base	Technique	Acc (%)	Sen (%)	Ppr (%)	Spe (%)
Data base I	HU-ANN [2]	98.01	75.10	71.34	98.96
	DCT-KNN [11]	99.90	98.80	98.90	99.95
	Krawtchouk-MD [6]	99.93	99.10	99.14	99.96
	Proposed	**99.96**	**99.50**	**99.52**	**99.98**
Data base II	HU-ANN [2]	94.91	38.88	35.76	97.34
	DCT-KNN [11]	99.20	90.46	91.14	99.59
	Krawtchouk-MD [6]	99.26	91.13	91.34	99.61
	Proposed	**99.47**	**93.58**	**93.62**	**99.72**
Data base III	HU-ANN [2]	95.55	46.54	40.71	97.68
	DCT-KNN [11]	99.59	95.13	95.34	99.79
	Krawtchouk-MD [6]	99.77	97.29	97.31	99.88
	Proposed	**99.86**	**98.33**	**98.38**	**99.93**

it is observed that overall recognition accuracy, sensitivity, positive predictivity and specificity of the proposed system are 99.96%, 99.50%, 99.52% and 99.98% respectively for database I, 99.47%, 93.58%, 93.62% and 99.72% respectively for database II and 99.86%, 98.33%, 98.38% and 99.93% respectively for database III. The results in Table II also indicate that the overall recognition performance of the proposed system is better compared to HU-ANN [2], DCT-KNN [11] and Krawtchouk-MD [6] mathod for all three databases.

V. CONCLUSION

This work proposes a new static hand gesture recognition system which deals with images of bare hands and allows to recognize gesture in illumination, rotation, position and size variation of gesture images. Homomorphic filtering and grayworld algorithm are used to normalize illumination variation of grayscale and color image respectively. Otsu and a skin color detection based segmentation algorithm are used to segment hand region from grayscale and color image and to provide binary silhouette. An image rotation technique by coinciding the 1^{st} principal component of the segmented hand gestures with vertical axes is proposed for rotation normalization. Morphological filtering technique is applied to reduce object noise from binary image and to obtain a well defined smooth, closed, and complete segmented hand gesture. A mixture of features (or combined features), by appending LCS features with block based features is proposed to represent the segmented binary static hand gesture image. Finally, the classification is performed using multiclass SVM classifier. The experiments are conducted on three different hand alphabet database to analyze the usefulness of proposed combined features representation for static hand gesture recognition and to evaluate the performance of the static gesture recognition system. Experimental results show that proposed combined features representation offers better recognition performance compared to LCS and block based features. The experimental results also indicate that the proposed system able to recognize static gesture with a recognition sensitivity of 99.50%, 93.58% and 98.33% for database I, database II and database III respectively which are better compared to eirlier reported methods.

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