Dynamic Hand Gesture Recognition of Arabic Sign Language using Hand Motion Trajectory Features

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Abstract - In this paper we propose a system for dynamic hand gesture recognition of Arabic Sign Language. The proposed system takes the dynamic gesture (video stream) as input, extracts hand area and computes hand motion features, then uses these features to recognize the gesture. The system identifies the hand blob using YCbCr color space to detect skin color of hand. The system classifies the input pattern based on correlation coefficients matching technique. The significance of the system is its simplicity and ability to recognize the gestures independent of skin color and physical structure of the performers. The experiment results show that the gesture recognition rate of 20 different signs, performed by 8 different signers, is 85.67%.

Keywords : arabic sign language; skin color segmentation; gesture recognition; face detection; hu moments; correlation coefficients.

GJCST-F Classification: I.4.m

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Mohamed S. Abdalla[α] & Elsayed E. Hemayed[σ]

segmentation; gesture recognition; face detection; hu moments; correlation coefficients.*

I. Introduction

A gesture is a form of non-verbal communication made with a part of body, used instead of or in combination with verbal communication. Gestures are ambiguous and incompletely specified. Similar to speech and handwriting, gestures vary from a person to another, and even for the same person between different instances. Arabic Sign Language (ArSL) is a dominant Sign Language of the deaf community in Egypt, and in many other countries of the Arab world. Recognition of the gesture is difficult because of spatial variation and temporal variation among gestures performed by different signers.

Many researches have been conducted to provide appropriate methods and tools to enable deaf people to interact easily and efficiently with regular people. Various sign language recognition systems have been developed by manufacturers around the world to serve these people but they are neither flexible nor cost-effective for the end users who have difficulties communicating in verbal form. Our goal is to help these less fortunate people to mingle in the society. Thus, there is a need for a system that helps in the communication between the deaf and regular hearing people. To realize this system, an efficient gesture recognition method is needed, which recognizes the sign language video stream for particular gesture. Since

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sign language is a native language, our research is targeting Arabic sign language (ArSL).

The remainder of this paper is organized as follows; a short survey of related work is presented in Section 2. Our proposed system architecture is explained in Section 3. Followed by Section 4 where we discuss the experimental results. We conclude in Section 5.

II. Related Work

Hand gesture recognition was firstly proposed by Krueger [1] as a new form of human computer interaction in the middle of the seventies, and there has been a growing interest in it recently. Hand gestures can be classified into two categories: static and dynamic. A static gesture is a particular hand shape and pose, represented by a single image. A dynamic gesture is a moving gesture, represented by a sequence of images. Our approach focuses on the recognition of dynamic gestures.

Many researchers have proposed different methods to recognize hand gestures. Two main approaches were introduced to support these researches; glove-based methods [2], [3] and vision-based methods [4], [5]. The glove based system [6], [2] relies on electromechanical devices. Here the person must wear some sort of wired gloves that are interfaced with many sensors. Vision-based recognition systems do not use special device such as glove, special sensor, or any additional hardware except simple webcam, image processing, and artificial intelligence to recognize and interpret hand gestures [7], [8]. In addition, the user's motions are not limited comparing with the use of glove. On the other hand, vision based systems have problems such as illumination changes, data clutter and hand occlusion due to hand motion. Several researches in vision-based approaches were introduced to overcome these problems.

The system developed by Hamada et al. [9] introduces a hand shape estimation approach to overcome occlusion by using multi-ocular images using two cameras. Tanibata et al. [10] provided a prototype approach based on feature extraction to solve hand occlusion problem for Japanese sign language recognition. The system developed by Wu et al. [11] presented real-time face/hand localization by using

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color-based image segmentation and non-stationary color-based target tracking using appearance based statistical.

The system developed by Tomasi et al. [12] presented 3D tracking for hand finger spelling motions by using a Real-time combination of 2D image classification and 3D motion interpolation using hand model based statistical. The system developed by Ye et al. [13] presented classifying manipulative and controlling gestures by computing 3D hand appearance using a region based coarse stereo matching algorithm.

The system developed by Lin et al. [14] presented tracking the articulated hand motion in a video sequence by searching for an optimal motion estimate in a high dimensional configuration space using hand model based statistics. The system developed by Feris et al. [15] proposed an approach to exploit depth discontinuities for finger spelling recognition to differentiate between similarities of some signs by using multi flash camera. The system developed by Barczak et al. [16] presented a real-time hand tracking by appearance based statistics using the Viola-Jones method. This system is implemented only in a restricted single posture (hand palm). The system developed by Zhou et al. [17] presented articulated object (e.g. body/hand postures) recognition using inverted indexing in an image database using local image features hand model based statistics. The system developed by Salleh et al. [18] provided a good idea to convert sign language to voice recognition based on feature extraction and HMM from grey scale images. Dreuw [19] investigated the use of appearance based features for the recognition of gestures using video input. He used 1st time derivative of original images thresholded by their skin probability and a camshift tracker. A finger spelling recognition method by using distinctive features of hand shape proposed by Tabata et al. [20] The system developed by Qiong et al. [21] presents detailed description of a real-time hand gesture recognition system using embedded DSP board and image processing approaches. The system developed by Foong et al. [22] proposed a sign to voice system prototype which is capable of recognizing hand gestures by transforming digitized images of hand sign language to voice using Neural Network approach. Zabulisy et al. [23] proposed a vision-based hand gesture recognition system for Human-Computer Interaction.

In the system developed by Xin-Yan et al. [5], a method of gesture segmentation from the video image sequence based on monocular vision is presented by skin color and motion cues. The system developed by Paulraj et al. [24] presented a simple sign language recognition system that has been developed using skin color segmentation and Artificial Neural Network. The system developed by Hsieh et al. [25] presented a simple and fast motion history image based method. In the system developed by Jiatong et al. [26] the dominant movement direction of matched SURF points in adjacent frames is used to help describing a hand trajectory without detecting and segmenting the hand region. The system developed by Mekala et al. [27] proposed an architecture using the neural networks identification and tracking to translate the sign language to a voice/text format. Zaki and Shaheen [28] presented a novel combination of vision based features in order to enhance the recognition of underlying signs. They used three features; kurtosis position, principal component analysis PCA, and motion chain code. Several systems have been proposed specifically for the Arabic sign language. The system developed by Mohandes [29] introduced a prototype system based on support vector machine (SVM) and an automatic Translation system to translate Arabic Text to Arabic Sign Language. An Arabic sign language translation system on mobile devices was introduced by Halawani [30]. The system developed by Farouk et al. [31] represent a multistage hierarchical algorithm for hand shape recognition using principal component analysis (PCA) as a dimensionality reduction and a feature extraction method. Al-Roussan et al. [32] presented an automatic Arabic sign language recognition system based on hidden Markov models. He used the discrete cosine transform to extract features from the input gestures by representing the image as a sum of sinusoids of varying magnitudes and frequencies. He used 30 isolated words from the Standard Arabic sign language database where gloves worn by the participants were marked with six different colors at six different hand regions.

The system developed by Nashwa et al. [33] presented an automatic translation system of gestures of the manual alphabets in the Arabic sign language. Hemayed and Hassanien [34] Dynamic Hand Gesture Recognition of Arabic Sign Language Using Hand Motion Trajectory Features introduced a new Arabic finger spelling technique that uses the edges of a segmented hand gesture as a feature vector and probabilistic neural networks to measure the similarity between the signs feature vectors.

From the previous survey of related works we find that the vision based approach is widely used for sign language recognition because of it its naturalness and low cost. Pervious works of sign language recognition systems have some constraints; these constraints affect the reliability and flexibility of these systems. There is a still a room for improving the accuracy of recognition systems. Moreover, most pervious works for Arabic sign language (ArSL) recognition systems deal with static hand posture.

The proposed system tries to eliminate some of previous systems' limitations to make the recognition process more practical and reliable in various conditions and applications. We are addressing mainly dynamic hand gesture of Arabic sign language.

III. System Architecture

Our Arabic sign language recognition system, as shown in Fig. 1, consists of three main modules; hand extraction, features extraction, and gesture recognition module. The hand extraction module extracts the hand area from the input video stream. The feature extraction module calculates 14 features for the hand motion trajectory. The features of the reference gestures are stored in the system database in the learning phase. Then the object recognition module uses correlation coefficient to match the features of the input gesture to the stored ones. More details about each module are discussed in the next sections.

a) The Hand Extraction Module

In this module, the hand area is extracted from the full color image. First the system captures video stream of gesture. From this captured frames we detect the face using Haar classifier [35]. The detected face location is replaced by a black ellipse to eliminate the confusion between the hand and the face. The system executes accurately even if there are multiple faces in the image. The process of face detection and removal is as shown in Fig. 1(a).
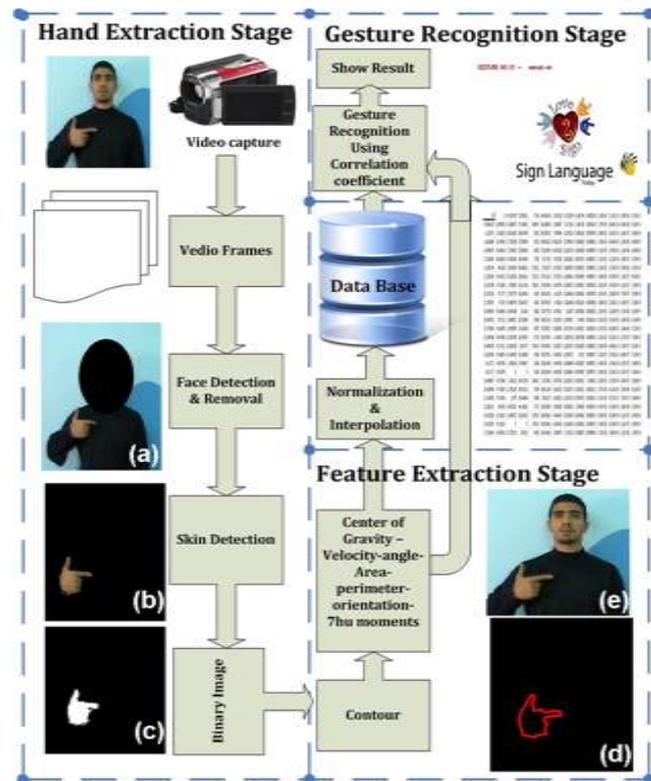

Figure 1 : Gesture recognition system architecture (a) Face detection and removal, (b) Hand extraction using YCbCr skin color detection Algorithm, (c) Hand extraction with binary image, (d) The contour of the hand blob & (e) The center of gravity

Second, the image is converted into YCbCr color space. A skin profile [5] is used to detect the skin color from the YCbCr image. In order to detect the hand from the YCbCr color image, we use the Cb and Cr components to define the skin profile. The thresholds are chosen by defining the lower and upper value of Cb skin color [Cb_min, Cb_max], and the lower and upper value of Cr skin color Color [Cr_min, Cr_max] [36]. The process of skin color detection to extract hand using YCbCr color space is as shown in Fig. 1(b). Then morphological operations (opening followed by dilation) [2] are used to fill in small disconnected areas. The result of this operation is a binary image that contains connected areas representing the hand blob. Fig. 1(c) shows the binary image, which shows only the hand area as white color in black background.

b) Feature Extraction Module

The output of the hand extraction stage is a binary image, which shows only the hand blob. The hand features extraction subsystem takes this binary image and find the contour shape of the hand blob as shown in Fig. 1(d). From that contour, we calculate 14 features. These features are the center of gravity for that contour (Fig. 1(e)) and then tracking the movement of hand in each frame to calculate the velocity of the hand movement and angle. In addition, the area, perimeter, orientation and 7-Hu moments features for contour shape are calculated. The details of the features calculations are as follows:

i. *Center of Gravity, Velocity and Angle Calculations*

The zeroth and first order moments [37] contain information about the center of gravity (Xc , Yc) of the object, where:

$$x_c = \frac{M_{1,0}}{M_{0,0}} \tag{1}$$

$$y_c = \frac{M_{0,1}}{M_{0,0}} \tag{2}$$

From one frame to the next, the center is moving, say from (X1, Y1) to (X2, Y2). Then the velocity and the angle of the hand motion can be calculated as follows:

$$V_x = X_1 - X_2 \tag{3}$$

$$V_y = Y_1 - Y_2 \tag{4}$$

$$V = \sqrt{V_x^2 + V_y^2} \tag{5}$$

$$\theta = \tan^{-1}\left(\frac{Y1 - Y2}{X1 - X2}\right) \tag{6}$$

Where ϴ is the angle and Vx, Vy are the corresponding velocity in x-axis and y-axis.

ii. *Area (A)*

The area of a contour is the number of pixels inside this contour. The zeroth order moment describes the area A of the contour of object.

$$A = M_{0,0} \qquad (7)$$

iii. *Perimeter (T)*

The perimeter of a contour is the length of curve or boundary of this contour. The contour perimeter of the object is calculated as the sum of lengths of segments between subsequent points of boundary.

$$T = \sum_{i=1}^{N-1} d_i = \sum_{i=1}^{N-1} |x_i - x_{i+1}| \qquad (8)$$

Where X1,……….., XN is the boundary coordinate list.

iv. *Orientation*

The second order moments known as the moments of inertia, can be used to determine an important image feature, orientation. In terms of moments, the orientations of the principal axes, Θ, are given by Horn [38]:

$$\theta = \frac{1}{2} \tan^{-1} \left(\frac{2M_{1,1}}{M_{2,0} - M_{0,2}} \right) \qquad (9)$$

v. *Seven Hu Moments*

Hu [37] defines the seven functions, computed from central moments through order three, that are invariant with respect to object scale, translation and rotation. Therefore, these seven Dynamic Hand Gesture Recognition of Arabic Sign Language Using Hand Motion Trajectory Features functions are good features to describe the objects.

The same Gestures may vary between performers and even for the same performer between different instances. Neither all the gestures have the same numbers of frames nor have the same start point. To provide better matching criteria for pattern matching, all the data should be normalized and interpolated. These two processes convert the original data sets into a new form, which provides better matching criteria.

c) *The Gesture Recognition Module*

There are several pattern recognition techniques used for gesture recognition. In this paper we use correlation coefficient [26] technique. Correlation coefficient is a simple statistical method with short processing time and it needs only one reference sample to learn each gesture.

If we have a series of n measurements of A and B written as Ai and Bi where i = 1, 2, …, n, then the

sample correlation coefficient can be used to estimate the population correlation r between A and B as follows:

$$r = \frac{\sum_{i=1}^{n} \left((A_i - \overline{A})(B_i - \overline{B}) \right)}{\sqrt{\sum_{i=1}^{n} (A_i - \overline{A})^2 \cdot \sum_{i=1}^{n} (B_i - \overline{B})^2}} \qquad (10)$$

Where $\overline{A}$ and $\overline{B}$ are the sample means of A and B.

In our system, A refers to the data set of the input gestures, B refers to the data set of the reference gestures stored in our database, and n is the number of frames in each gesture. We calculate the correlation coefficients between the input gesture and the reference gestures. The correlation coefficient is calculated for each feature separately.

Then we count, for each gesture, number of correlation coefficient that is greater than a predefined threshold. In our experiments, the used threshold was 0.65. Finally the gesture with the highest count is selected as the matched gesture and its corresponding text is shown to the user.

IV. Results and Discussion

Due to the unavailability of a dataset for dynamic gestures from Arabic sign language, we had to build our own gestures database. We collected 20 different signs (Table 1) from eight different signers (seven males and one female) at different situations with resolution 720×480, as shown in Fig. 2.

Table 1 : List of Selected Gestures

Gesture No.	Gesture name in Arabic	Gesture meaning in English
G1	ما اسمك؟	WHAT IS YOUR NAME?
G2	غني	RICH
G3	شجاع	BRAVE
G4	بطاطس	POTATO
G5	بيض	EGGS
G6	نحيف	EMACIATED
G7	لبن	MILK
G8	ليل	NIGHT
G9	إعصار	hurricane - Tornado
G10	رسول .	PROPHET
G11	مدينه 6 أكتوبر	6 october CITY
G12	ضابط	OFFICER
G13	مهم	IMPORTANT
G14	مدير	MANAGER
G15	نادي	CLUB
G16	غائب	ABSENT
G17	ينزل	DESCEND- GET DOWEN
G18	يريد	WANT - DESIRE
G19	يعطي	GIVE
G20	بسرعه	RAPIDLY - QUICKLY

Figure 2 : Eight different singers for our Arabic sign language dataset

We collected 63 feature vectors for each gesture. Thus in total our database has 1260 feature vectors. Only 20 gestures were used for training, one from each gesture. The proposed system is implemented on a PC with 2.0GHz CPU and 2G memory running Windows 7. The system is coded by C#, and the OpenCV SDK is used. The overall processing speed was 10-30 frames/Sec. Thus it can be used in a real time interaction.

In our experiment, we measure the discrimination effectiveness of the proposed system by testing the recognition of each sign. Our results indicate that the recognition rate was between 80% and 100% with an average of 85.67%. Fig. 3 shows the similarity matrix between the input and reference gestures. From the shown graph, it is clear that all of the signs have high similarity with its counterpart along the diagonal axis with some minor similarity off the diagonal axis.
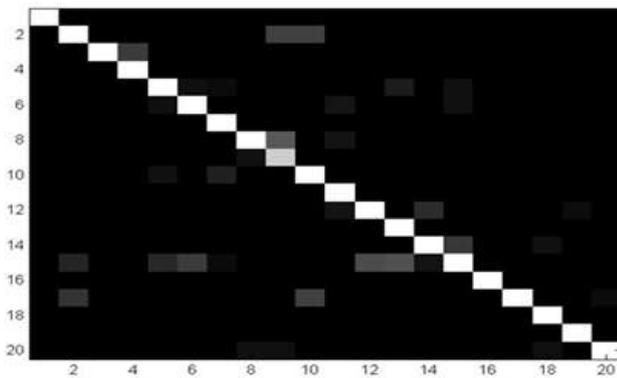

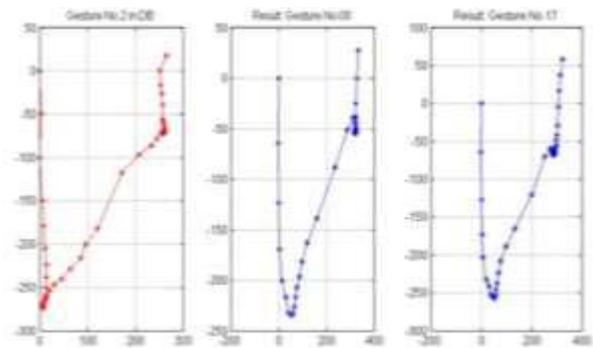*Figure 3 :* The similarity matrix for our proposed system

Figure 4 : The motion trajectory of gesture 2, 8 and 17. The graph shows the position of the hand's center of gravity at consecutive frames

We also analyzed the misclassification cases to measure the consistency of the proposed system. Fig. 4 shows the motion trajectory of three gestures; No 2, 8 and 17, that our system confuses them. These three gestures are very similar and their motion trajectories are very similar too. Several gestures in the Arabic sign language look similar and could be difficult to a computer vision system to differentiate between them.

In another experiment, we apply our system to the RWTH dataset developed and tested by Dreuw [19]. RWTH dataset is a German finger spelling alphabet database and it contains 35 gestures with video sequences for the signs A to Z and SCH, the German umlauts Ä, Ö, Ü and the numbers from 1 to 5. Dreuw [19] achieved an error rate of 87.1% and was able to improve it to 44%.

Using our proposed system, we were able to achieve a better error rate of 27.6%. It was not possible to compare our work with several available systems, because they differ in many aspects such as the type of data acquisition; direct measurement or vision-based. Even in the vision based approach some systems require the signer to wear colored gloves. Another problem arises from the lack of a common database for the evaluation of sign language recognition systems. Almost all databases used by the different research groups are not publicly available. Additionally, the available databases differ in language, vocabulary size, grammar restriction and selection of signs.

V. Conclusion

We proposed a new gesture recognition system that can recognize the dynamic Arabic Sign Language gestures independent of skin color and physical structure of signers. In addition, the Dynamic Hand Gesture Recognition of Arabic Sign Language Using Hand Motion Trajectory Features system works in different places with normal intensity of light. The proposed features, measured from the motion trajectory of the right hand, were able to encode the gesture and to differentiate between 20 different Arabic gestures

collected from eight different signers, with an average recognition rate of 85.67%. The error rate was mainly due to the high similarity between the gestures.

The proposed system was able to improve the error rate in recognizing the difficult RWTH dataset from 44% to 27.6%. In future work we will search for other clues to be able to increase the recognition accuracy especially in case of highly similar gestures. Also, handling gestures that use both hands or interfere with the face will be addressed in future work.

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