USER INDEPENDENT SYSTEM FOR RECOGNITION OF HAND POSTURES USED IN SIGN LANGUAGE

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Keywords: Hand posture recognition, Moments, Shape, Sign language.

Abstract: A new signer independent method of recognition of hand postures of sign language alphabet is presented in this paper. We propose a new geometric hand postures features derived from the convex hull enclosing the hand's shape. These features are combined with the discrete orthogonal Tchebichef moments, and the Hu moments. The Tchebichef moments are applied on the external and internal edges of the hand's shape. Experiments, based on two different hand posture data sets, show that our method is robust at recognizing hand postures independent of the person performing them. The system obtains a good recognition rates, and also performs well compared to other hand user independent posture recognition systems.

1 INTRODUCTION

The most important way of communication in the deaf community is the sign language. The goal of the sign language recognition is to transcribe automatically the gestures of the sign language into significant text or speech. The sign language is a collection of gestures, movements, postures, and facial expressions corresponding to letters and words in natural languages. The works in automatic Sign Language Recognition (SLR) research has happening about twenty years ago particularly for American (Starner and Pentland, 1996), and Australian (Kadous, 1996). Since lot of systems have been developed for different sign languages including: Arabic sign language (Al-Jarrah and Halawani, 2001), French sign language (Aran et al., 2009). German sign language (Dreuw et al., 2008)

Sign language recognition (SLR) can be classed into isolated SLR and continuous SLR and each can be further classified into signer-dependent and signer-independent systems. These systems can be divided into major classes. The first class relies on electromechanical devices that are used to measure the different gesture parameters. Such systems are called glove based systems. These systems have disadvantages to be complicated and less natural. The second class exploits machine vision and processing techniques to create visual based hand gesture and posture recognition systems. This second class is the class of vision based systems. A variety of methods and algorithms has been used for solving the problem of SLR, include distance classifiers, template matching, conditional random field model (CRF) dynamic time warping model (DTW), Bayesian network, neural networks, fuzzy neural networks, Hidden Markov models, geometric moments, Discrete Cosine Transformation (DCT). Size functions.

However, the accuracy of most methods treating the problem of hand posture recognition depends on the training data set of the system used. Most performance measures where results of signer dependent experiments are carried out by testing the system on subjects that were also used to train the system. This is due to the anatomic particularity of each person. An ideal system of hand posture recognition should be able to give a good recognition separately from the training data set.

Consequently, several user independent hand posture recognition systems were developed. Most of these systems perform their training data with different subjects from the subjects of the test data: In (Al-Roussan and Hussain, 2001) the authors developed a system to recognize isolated signs for 28 alphabets from Arabic sign language (Arsl) using colored gloves for data collection and adaptive neuro-fuzzy inference systems (ANTFS) method. A Recognition rate of 88%was achieved. Later, and on a similar work the recognition rate increased to 93.41 using polynomial networks (Assalaeh and Al-Roussan, 2005). (Treisch and Von der Malsburg, 2002) proposed a method using elastic graph matching with a recognition rate of 92.9% for classifying 10 hand postures. (Kelly et al., 2010) proposed a user independent system of hand posture recognition based on the use of weighted eigenspace size functions, the method achieved a recognition rate of 93.5 tested on Treisch data set.

This paper proposes a Recognition system for static sign language alphabets. The system is user independent and uses no gloves or any other instrumented devices. We propose a new hand posture features extracted from the convex hull enclosing the hand's shape. These features are combined with the discrete orthogonal Tchebichef moments and the geometric Hu moments. The experiments are based on two separate data sets. The system obtains a good recognition rate for all data sets.

2 PROPOSED APPROACH

The proposed system is designed to recognize static signs of sign language alphabets. The Figure1 shows the block diagram of the proposed recognition system.

2.1 Preprocessing

To extract the external contour of the images, we followed these steps at first the image segmentation is carried out using the global threshold filter, after the morphological operations (erosion and dilation) are applied to the image and finally using the region of the hand gesture we extract the external hand contour. As we can see in the Figure2.

The internal and external detection process is performed using the adaptive threshold filter.

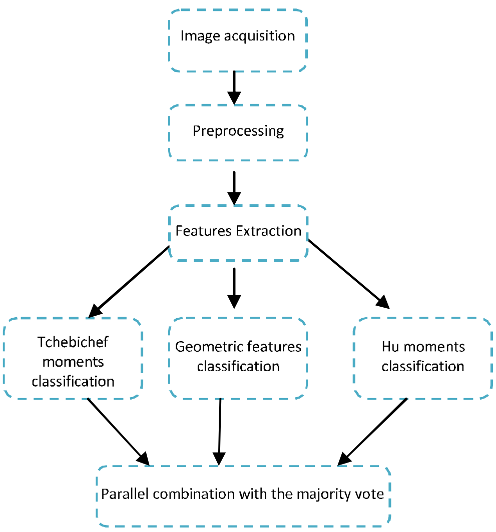

Figure 1: Proposed system.

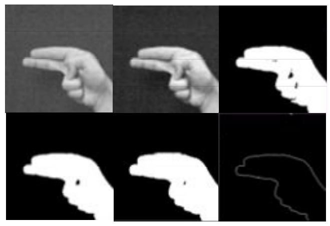

Figure 2: Example of contour extraction from G from Treisch data set.

2.2 Features Extraction

In the proposed approach, three types of the feature vectors are computed, the orthogonal Tchebichef moments calculated from the internal and external edges of the hand, the geometrical features vectors, and the statistical features in this Hu moments calculated the external hand contour.

2.2.1 The Tchebichef Orthogonal Moments

Orthogonal moments are good signal descriptors with their low order components are sufficient to provide discriminant power in pattern or object recognition.

The discrete Tchebichef moments T_{pq} of order $(p+q)$ of $(M \times N)$ discrete space image are defined as in (Mukundan et al., 2001):

$$T_{pq} = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \tilde{t}_p(x)\tilde{t}_q(y)f(x,y) \tag{1}$$

Where $\tilde{t}_p(x)$ and $\tilde{t}_q(y)$ are the normalized Tchebichef polynomials defined as

$$\tilde{t}_p(x) = \frac{t_p(x)}{\sqrt{\tilde{\rho}(p,M)}} \; ; \; \tilde{t}_q(y) = \frac{t_q(y)}{\sqrt{\tilde{\rho}(q,N)}} \tag{2}$$

With

$$\tilde{\rho}(\rho,M) = \frac{M(1-\frac{1}{M^2})(1-\frac{2^2}{M^2})\ldots(1-\frac{p^2}{M^2})}{2p+1} \tag{3}$$

The discrete Tchebichef polynomials $t_p(x)$ can be found in (Erdelyi et al., 1953).

2.2.2 The Geometric Features Vectors

To describe hand posture we propose some geometric features using the convex hull enclosing the hand shape. This geometric feature set contains three features:

1) The Relative Area

The relative area represents the ratio between the area of the hand shape and the area of the convex hull. It is defined as:

$$\mathrm{Re}\,l\ \mathrm{Area} = \frac{Area_{hand\ \mathrm{shape}}}{Area_{Convex\ \mathrm{hull}}} \quad (4)$$

2) The Relative Minimum Distance

This feature is defined as:

$$\mathrm{Re}\,l\ \mathrm{D_{min}} = \frac{D_{\min}}{Lg} \quad (5)$$

Where $D_{\min}$ represents the distance between the center of gravity of the hand and the point $P_{\min}$ .The point $P_{\min}$ is the closest vertex of the convex hull from the center of gravity of the hand, and Lg the length of the bounding box enclosing the hand shape.

3) The relative Maximum Distance

This feature is defined as:

$$\mathrm{Re}\,l\ \mathrm{D_{max}} = \frac{D_{\max}}{Lg} \quad (6)$$

Where $D_{\max}$ represents the distance between the center of gravity of the hand and the point $p_{\max}$. The point $p_{\max}$ is the furthest vertex of the convex hull from the center of gravity of the hand.
The Figure 3 illustrates this features.

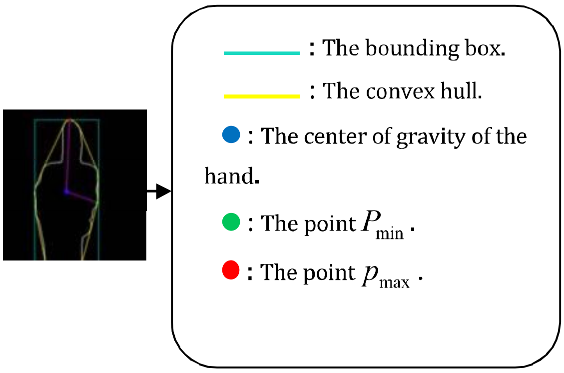

Figure 3: Illustration of the geometric features.

2.2.3 Hu Moments

Hu moments (Hu, 1962), which are a reformulation of the non-orthogonal centralized moments, are a set of transition, scale, and rotation invariant moments.

3 DATA COLLECTION

We evaluate our techniques using two separate data sets.

3.1 Arabic Sign Language Database

The data set consists of 30 hand signs from the Arabic sign language (Arsl) alphabet.

The hand postures were performed by 24 different subjects against uniform background and with different scaling.

3.2 Jochen-Treisch Static Hand Postures Database

The second data set is a benchmark database called the Jochen-Treisch static hand postures database (Treisch and Von Der Malsburg, 2002). The system proposed was tested on hand images with dark and light backgrounds.

4 EXPERIMENTAL RESULTS

The classification of the hand postures is performed using the parallel combination with the majority vote. The Table1 presents the performance of the system for the Treisch data set with the scenario of (Just et al., 2006) 8 subjects for training dataset and 16 subjects for the test dataset with light and dark background respectively.

Table 1: Classification performance for the Treisch database (light and dark background).

Backgrounds	Recognition rate
Light background	97,5%
Dark background	88,6%
Global recognition rate	93.1

The classification of Arsl sign language alphabets achieved a recognition rate of 94.67%, with the scenario of 4 subjects for training data set and 20 subjects for the test data set. The result obtained by the proposed system performs well knowing that the best recognition rate obtained until now in Arabic sign language alphabet is equal to 93,41 (Assaalaeh and Al-Roussan, 2005), and the system developed used colored gloves.

5 CONCLUSIONS

In this paper we present a new signer independent system of hand postures recognition. It is a vision based system that uses no glove or any other devices. The method is based on the use of geometrical and statistical features. The system proposed performs well in the classification of hand postures from the Arabic sign language alphabets.

A recognition rate of 94.67% was achieved. We showed good performance of our system on the benchmark Treisch hand postures database.

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