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RESEARCH ARTICLE

HAND GESTURE RECOGNITION USING GRADIENT ORIENTATION

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ABSTRACT

Hand gesture recognition system can be used for providing the interface between computer and human using hand gestures. The main objective of the present work is to develop algorithms for the recognition of thirty six static hand gestures in the American Sign Language (ASL). By employing a pattern recognition technique in which the orientation histogram is used as a feature vector for gesture classification and interpolation accurate results are obtained.

INTRODUCTION

Hand gesture recognition system can be used for interfacing between computer and human using hand gesture. This work presents a technique for a human computer interface through hand gesture recognition that is able to recognize 36 static gestures from the American Sign Language hand alphabet. The objective of this paper is to develop an algorithm for recognition of hand gestures with reasonable accuracy. Recently, there has been a surge of interest in recognizing human hand gestures. Hand-gesture recognition has various applications like computer games, machinery control (e.g. crane), language for speech and hearing impaired and thorough mouse replacement. One of the most structured sets of gestures belongs to sign language. In sign language, each gesture has an assigned meaning (or meanings). Computer recognition of hand gestures may provide a more natural-computer interface, allowing people to point, or rotate a CAD model by rotating their hands. Hand gestures can be classified in two categories: static and dynamic. A static gesture is a particular hand configuration and pose, represented by a single image. A dynamic gesture is a moving gesture, represented by a sequence of images. We will focus on the recognition of static images [1] to [3].

APPLICATIONS

Creating a proper sign language (ASL – American Sign Language) dictionary is not the desired result at this point. This would combine advanced grammar and syntax structure understanding of the system, which is outside the scope of this work.

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The ASL will be used as the database since it's a tightly structured set. From that point further applications can be suited.

American Sign Language

ASL is the language of choice for most deaf people in the United States. ASL is one of the many sign languages of the world. ASL consists of approximately 6000 gestures of common words with finger spelling used to communicate obscure words or proper nouns [4] to [6]. Finger spelling uses one hand and 26 gestures to communicate the 26 letters of the alphabet signs which can be seen in Fig.1 and 9 gestures to communicate the 9 digits can be seen in Fig. 2 below.

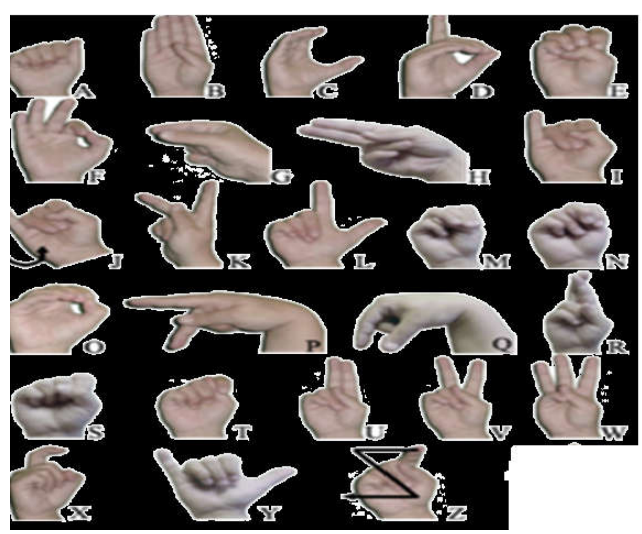

Fig. 1. American Sign Language(ASL) alphabets from A to Z

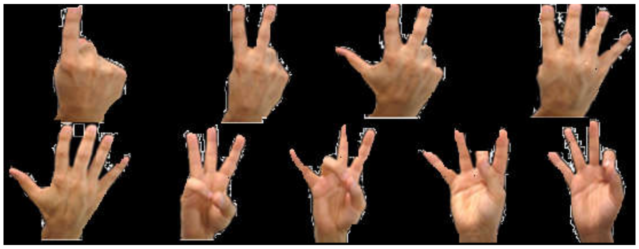

Fig. 2. American Sign Language(ASL) digits from 1 to 9

Background

Research on hand gestures can be classified into three categories. The first category, glove based analysis, employs sensors (mechanical or optical) attached to a glove that transducers finger flexions into electrical signals for determining the hand posture. The second category, vision based analysis, is based on the way human beings perceive information about their surroundings. It is probably the most difficult to implement in a satisfactory way. The third category, *analysis of drawing gestures*, usually involves the use of a stylus as an input device. Analysis of drawing gestures can also lead to recognition of written text.

Goals

The scope of this investigation is to create a method to recognize hand gestures, based on a pattern recognition technique; employing histograms of local orientation. The orientation histogram will be used as a feature vector for gesture classification and interpolation.

METHODOLOGY

The present investigation is carried out by using MATLAB. MATLAB is an interactive system whose basic data element is an array that does not require dimensioning. This allows us to solve many technical computing problems, especially those with matrix and vector formulations. In a fraction of time it would take to write a program in a scalar non-interactive language such as C or Fortran. The reason for selecting the MATLAB tool for the development of this paper is its toolboxes. Toolboxes allow you to *learn* and *apply* specialized technology. Toolboxes are comprehensive collections of MATLAB functions (M-files) that extend the MATLAB environment to solve particular classes of problems. It includes among other image processing and neural networks toolboxes.

Approach

The images were taken from the ASL database on the Internet. Three operations were carried out in all of the images. They were converted to grayscale, the background was made uniform and applied three types of Blurring methods (Gaussian, Motion and Smart) to each image [7]. The final form of the database is Fig. 3.

Training set

There are thirty six training sets of images, each one containing three images. Each set originates from a single image for testing.

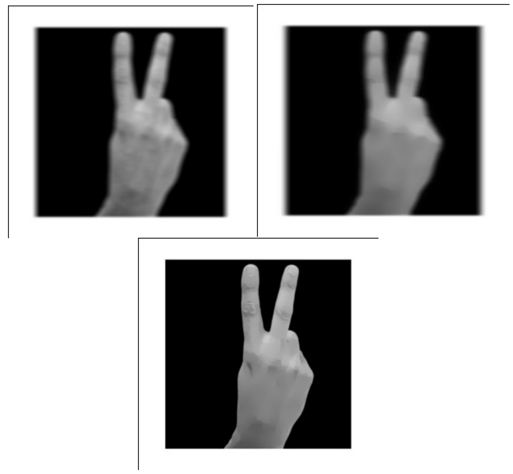

Fig. 3. Blurred images for the test image database (*Gaussian Blur, Motion Blur , Smart Blur*)

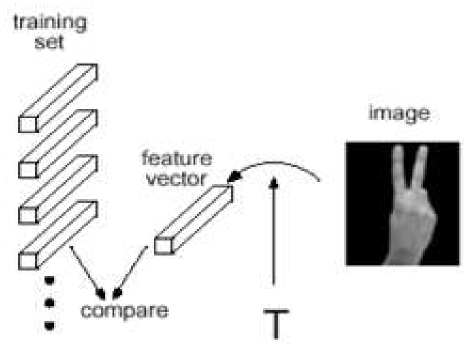

Fig. 4. Pattern Recognition System

The pattern recognition system that will be used can be seen in Fig. 4. Some transformation T, converts an image into a feature vector, which will be then compared with feature vectors of a training set of gestures. Histogram orientation has the advantage of being robust in lighting change conditions. If we follow the pixel-intensities approach certain problems can arise for varying illumination. Taking a pixel-by-pixel difference of the same photo under different lighting conditions would show a large distance between these two identical gestures. Orientation analysis should give robustness in illumination changes while histogramming will offer translational invariance. This method will work if examples of the same gesture map to similar orientation histograms, and different gestures map to substantially different histograms[8] and [9].

Orientation histograms

It is absolutely necessary that the gestures to be the same regardless of where they occur with the image boarders. To achieve this we will ignore position altogether, and tabulate a histogram of how often each orientation element occurred in the image. Clearly, this throws out information and some distinct images will be confused by their orientation histograms. In practice, however, one can choose a set of training gestures with substantially different orientation histograms from each other. One can calculate the local orientation using image gradients. We have used two 3 – tap x and y derivative filters. The outputs of the x and y derivative operators will be dx and dy. Then the gradient direction is atan (dx, dy). It was decided to use the edge orientation as the only feature that will be presented to the neural network. The reason for this is that if the edge detector was good enough it would have allowed us to test the network with images from different databases[6]. Another feature that could have been extracted from the image would be the gradient magnitude using the formula below

$$ds=\sqrt{dx^2 + dy^2}$$

This would lead to testing the algorithm with only similar images. Apart from this the images that are before resized should be of approximately the same size. This is the size of the hand itself in the canvas and not the size of the canvas. Once the image has been processed the output will be a single vector containing a number of elements equal to the number of bins of the orientation histogram. Fig. 5 shows the orientation histogram calculation for a simple image. Blurring can be used to allow neighboring orientations to sense each other.

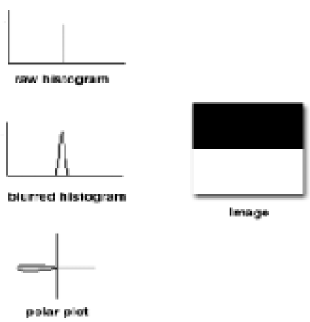

Fig. 5. Orientation histogram

The program is 'divided' into 5 steps:

STEP 1:

Read the image database. A *for* loop is used to read an entire folder of images and store them in MATLAB's memory. The folder is selected by the user from menus. A menu will firstly pop-up asking you to run the algorithm on test image set. Then a second menu will pop-up for the user to choose which ASL sign he wants to use.

STEP 2:

Resize all the images that were read in Step1 to 150x140 pixels. This size seems the optimal for offering enough detail while keeping the processing time low.

STEP 3:

Detection of the edges. As mentioned before two filters were used.

For the x direction x = [0 -1 1]

For the y direction y= [0 1 -1]'

In Fig. 6. We can see two images of the result of convolving an ASL sign of number 2 with the x-filter and y-filter. This is the only feature extracted from the images and it has to offer enough discrimination among them. From the images above it doesn't seem like a good edge detector. In fact it doesn't look like an edge detector.

STEP 4

Dividing the two resulting matrices (images) *dx* and *dy* element by element and then taking the atan ($\tan^{-1}$). This will give the gradient orientation.

The Gradient of an image is:

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

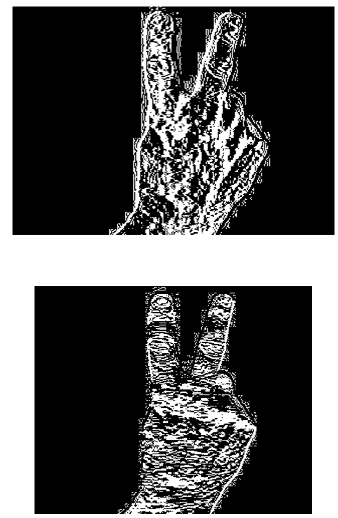

Fig. 6. X-Y filters

STEP 5:

Conversion of the column matrix with the radian values to degrees. This way we can scan the vector for values ranging from 0^o to 90^o. This is becuuse for real elements of X, atan(X) is in the range. This can also be seen from the orientation histograms where values come up only on the first and last quarter.Determination of the number of the histogram bins is another issue that is solved by experimenting with various values. We have tried with 18 20 24 and 36 bins. What was expected was the differentiation (or not) among the images. The smaller the vector the faster the processing. Finally, the actual resolution of each bin is set to 10^o , which means 19 bins.

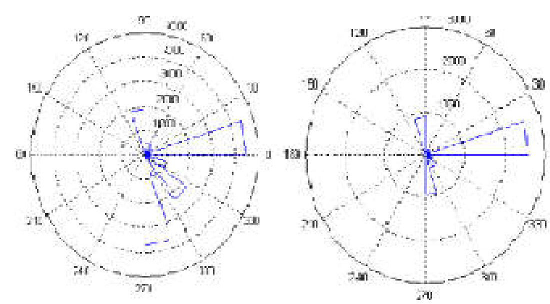

Fig. 7. Orientation Histogram for digit 2 in ASL

The algorithms were developed by keeping in mind MATLAB weaknesses. The major one is speed. MATLAB is perfect for speeding up the development process but it can be very slow on execution when bad programming practices have been employed. Nested loops slow down the program considerably. It is probably because MATLAB is built on loops. Therefore, unnecessary back-tracking is avoided and even some routines are written in full instead of using *for* loops. The code is quite compact in any case.

EXPERIMENTS AND RESULTS

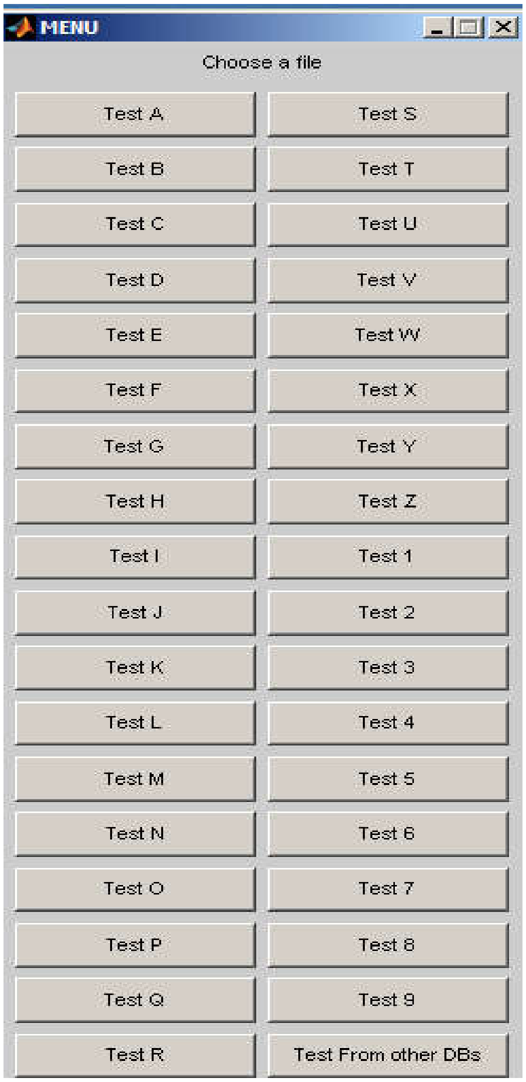

Fig. 8 shows the pop-menu for the user to select the particular alphabet or digit to display the hand gesture

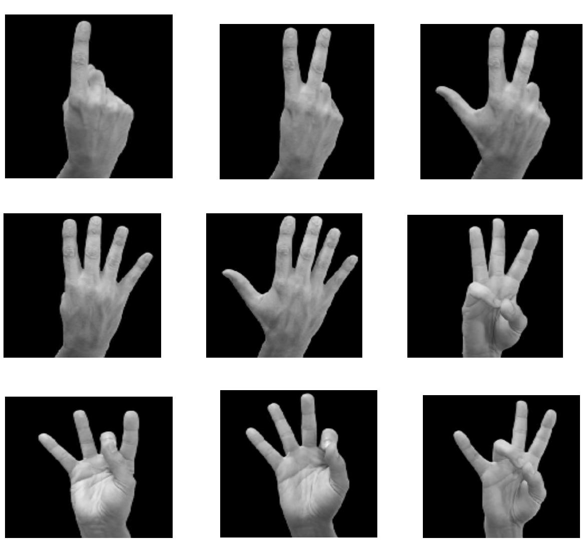

Fig. 9. The test results for digits from 1 to 9 when user chooses the option from pop-up menu

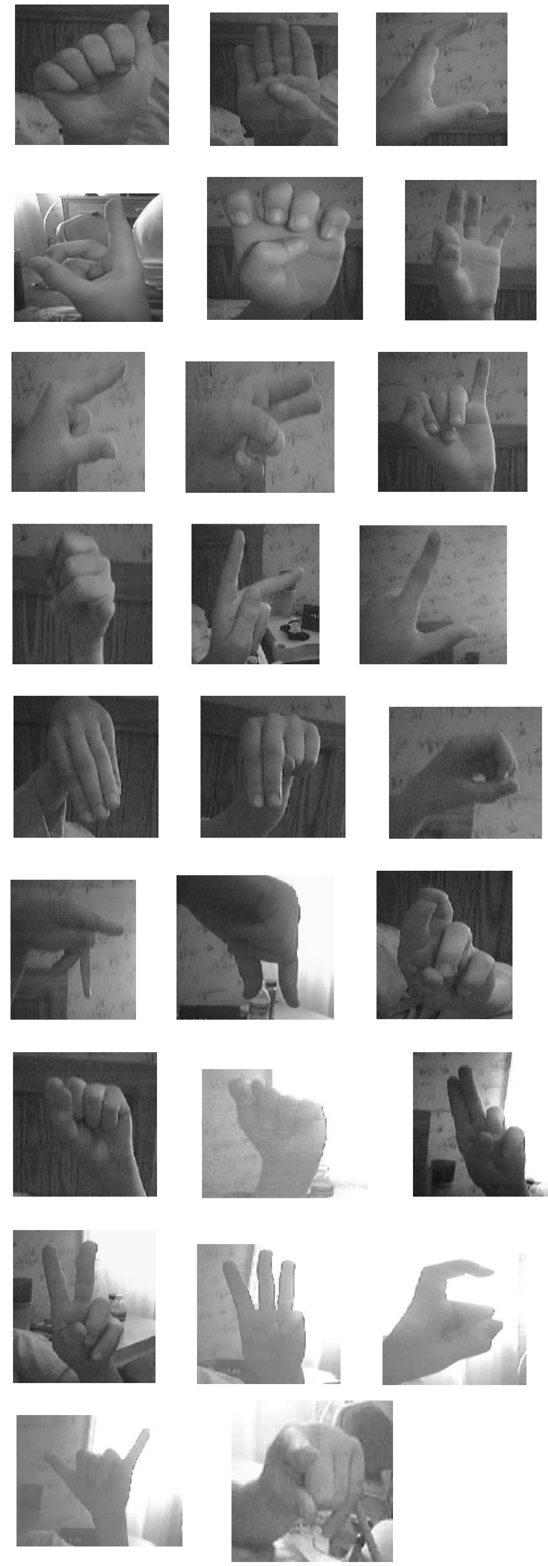

Fig. 10. Test results for alphabets from A to Z

Fig. 10, shows the test results for alphabets from A to Z when user chooses the option from pop-up menu

Conclusion

The motivation for the work is the idea of Gradient orientation. Many researchers found the idea interesting and tried to use it in various applications from hand recognition to cat recognition and geographical statistics. In other approaches of pattern recognition orientation histograms have used different ways of comparing and classifying images. Euclidean distance is a straight forward approach to it. It is efficient as long as the data sets are small and not further improvement is expected. As far as the orientation algorithm is concerned it can be further improved. The main problem is how effective differentiation one can achieve. This of course is dependent upon the images but it comes down to the algorithm as well. Edge detection techniques are keep changing while line detection can solve some problems.The main objective of this paper was the speed and the avoidance of special hardware. MATLAB is slower but allows its users to work faster and concentrate on the results and not on the design. Finally, it is concluded that the present methodology is excellent for problems of similar types.

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