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Hand Gesture Recognition using Improved Skin and Wrist Detection Algorithms for Indian Sign Language

Kavita Yadav
Teacher in the Secondary level school in Mumbai, MH, 400 002 India

Lalit P. Saxena*
Research Scientist in the Applied Research Section, Combo Consultancy, Obra India

Bilal Ahmed
PHP developer in Mumbai, MH, 400 002 India

Yugesh K. Krishnan
Software Developer in Mumbai, MH, 400 002 India

Abstract – The hand gestures add as a means to communication among human beings and some primates. The simplicity of the hand gestures or a sign language encompasses in a natural way of communicating mode. This paper presents novel skin and wrist detection algorithms to improving hand gesture recognition. The proposed method extracts features using principal component analysis in an image. This method uses a hybrid model implementing template matching and Euclidean distance methods for classification and recognition of Indian Sign Language symbols. The model includes recognition procedures like, skin detection, hand(s) selection, feature extraction, classification and recognition, components. This paper uses 24 different human hand(s) signs having 120 samples of each sign, obtained 93% as recognition rate. In future enhancements, the method would deal with dynamic hand(s) gestures and improve the recognition accuracy.

Index Terms – Hand gesture recognition, skin detection, hand selection, template matching, Euclidean distance.

1. INTRODUCTION

The Sign language interpretations enhance human computer interaction (HCI) as a new field of research [1], [2]. A PC with HCI interpretations to Indian Sign Language (ISL) system, aid in interacting hearing-disabled person to common people [3]. Despite of being the second highest populated nation in the world, ISL research attracts fewer brains. Sign Language comprise of gesture codes where each gesture reflects specific meaning defined for it. It is the only medium of communication for hearing-impaired people. Recent developments focused to reduce this problem for these people and expand its scope to other fields. For example, the American Sign Language, the British Sign Language, the Japanese Sign Language, and so on, are few worth mentioning [4].

Similar to regular languages, sign languages are natural languages having their own syntax, vocabulary and grammar that vary from region to region. It is also difficult in affording an experienced and qualified interpreter. In addition, this pushes hearing-impaired into isolation because non-deaf people avoid learning sign language. The systems that interpret sign language into text assist in reducing the difference between deaf and non-deaf. Automating sign language recognition will abridge vocal and non-vocal communications, similarly as fruitful as speech recognition systems.

The ISL is a communication medium for Indian hearing-impaired community; however, ISL research is still in its infancy [5]. The SL research involves human hands; it is an essential part in social cognition inference. The hands have fingers, and different areas of hand involved while working, the palm, the opisthenar (dorsal) and heel of the hand. It further consists of bones, arches, muscles, innervations, skin and variations.

A hand recognition system is a computer-vision application identifying a hand gesture from a digital image or a frame in a video sequence [6]. In simple words, matching special hand features in an image within a database. The system automatically identifies hand gesture present in images and video frames. The systems comprise skin detection, hand selection, features extraction and matching modules [7], [8]. Hand selection is an important step in such systems, since the performance of the system is dependent on hand selection reliability. A reliable hand selector finds and selects hands irrespective of position, scale, orientation, age or expression in a set of images or real-time video streaming.

Some algorithms find hands by separating landmarks or features, from a human hand image. For an instance, algorithm analyzes the position, size, and/or shape of the hands as features and match with other images [9]. While there are algorithms that normalize the hand images and save those images in the hand database, then a test image is compared within the database. Such systems employ template-matching technique using the representation of the hand features [10]. The proposed SL system study the signs derived through vision-based hand gesture recognitions. The system recognizes various alphabets of ISL by HCI obtaining better results in least possible time. This is an attempt to preserve ISL.

The rest of the organization of the paper is as follows. Section 2 summarizes state of the art methods in sign language recognition. Section 3 presents the proposed methodology of ISL recognition. Section 4 delivers the experimental results of ISL system, and section 5 concludes the paper.

2. STATE-OF-THE-ART

The previous methods use different combination of methods for the recognition of various human hand gestures. There are separate methods available for procedures like, hand segmentation, feature extraction and gesture recognition. Initially, the hand segmentation starts with the proper filtering of the skin. The skin-filtering method separates colored pixels comprising skin from non-skin regions, enabling hand separation from the background [11]. Based on the desired properties, feature extraction procedure expands to extracting features from the segmented hands. Some of the feature extraction methods include, principal component analysis (PCA) [12], support vector machines (SVM) [13], Euclidean distance [14], hidden markov model (HMM) [15] etc.

The Thai SL recognition proposed by [16] use Elman back propagation neural network (ENN) algorithm. It comprises of 30 hidden layers addition of input and output nodes, where input 14 nodes are the sensors in the data glove and output 16 nodes are the number of symbols. This method obtained the SL recognition accuracy of 94% single hand gestures. However, the method lacks at the skin filtering stage mainly affected by varying illumination.

The research work done on American and Japanese SL by [17] implemented ANN recognizing single hand gestures and obtained 93% accuracy. The system constitutes of the input, hidden and output layers having 20, 42 and 42 neurons respectively. PCA and back propagation algorithm were used to extract features—comprising shape and position of finger, and image direction represented by mean, Eigen values and vectors—and getting proper gesture recognition respectively. The features like shape, size, position and motion direction detected using PCA are the primary resource for the SL recognition in the video frames described by [18]. The adaptive boost algorithm derived by [19] reduced the inconsistencies in recognizing both hands and errors in overlapped hands. In order to minimize skin color misclassification, the researchers used color gloves for maximizing correct hands segmentation.

The generic Fourier descriptor and cosine descriptor are independent of invariances' like rotation, translation and scale aiding in correct feature extraction discussed by [20]. The SL recognition discussed by [21] considered only 15 hand gestures, doubting over polar space shift of hand if rotated images are made input. In order to eliminate such a shift this method only considered the Fourier coefficient magnitude. [22] extracted hand features in recognizing hand gestures with a recognition accuracy of 91%. The model considered shape, size, texture, orientation and finger features of the hand for recognition. In an innovative approach to recognize Korean SL, [23] used fuzzy logic accumulating various moving hand speeds, namely, small, medium (positive, negative), large (positive, negative), etc. The approach suffers from high computation complexity, for 3 gestures it achieved an accuracy of 94%.

Each method has its own advantages and disadvantages over a set of particular datasets. No algorithm performs better on every dataset; rather some perform better than the other for a specific dataset. The proposed method is an attempt to overcome some of the difficulties in hand gesture recognition for ISL. This method sufficiently reduces the computational time in recognizing bare hands rather than sensor-enabled hand gloves. The novelty of the method lies in its skin and wrist detection algorithms, it detects wrist(s) despite of various skin colors'. The following section discusses the method in detail and describes the algorithms with its full functionalities.

3. INDIAN SIGN LANGUAGE INTERPRETATION SYSTEM

The proposed system recognizes a human hand(s) gesture within an image captured through a web camera or previously stored in the dataset. The captured image is in color i.e., RGB (red, green, blue color channels), having both hand and background information. In order to successfully detect a hand in such an image, an effective skin detection algorithm is of much importance. The proposed method has a novel skin detection algorithm to hold this challenge. Once the skin of the hand is detected, it calls for hand detection in the image. However, there would be other components along with the hand, as a single connected component. The system finds and selects the largest connected component in the binary image, since this is the hand portion present in the image. This method separates the hand representing a symbol from the meaningless components in the image.

The image is then normalized to a predefined size; this reduces or stables the computational burden of uneven image sizes. After normalization, there is wrist detection step; the proposed wrist detection algorithm achieves this. The normalized image is input to the wrist detection algorithm. The specific wrist detection leads to feature extraction of the hand gesture symbol present in the image. This is further implemented through PCA in the features. Thus, classification and matching of ISL symbols to the hand gesture present in the image is recognized. Fig. 1 present the Indian Sign Language interpretation system.

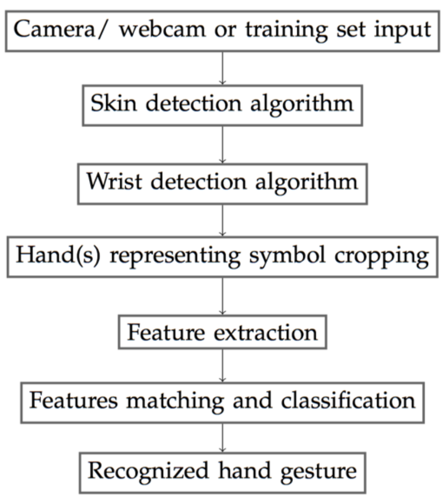

Figure 1 The Indian Sign Language interpretation system

3.1. Hand skin detection

The ISL interpretation system detects and separates skin regions from non-skin regions in the input image. The skin detection algorithm (1) effectively detects human hand(s) in the image, see Figure 2. This algorithm is an improved version of the color skin detection algorithm implemented by [11]. The implementation of the procedure and the color conversion equations are provided here, where color conversions adhered by the equations, [3].

$$M = \max(R, G, B) \tag{1}$$

$$m = \min(R, G, B) \tag{2}$$

$$C = M - m \tag{3}$$

$$H' = \begin{cases} undefined, & if \quad c = 0 \\ \frac{G-B}{C} mod\ 6, & if \quad M = R \\ \frac{B-R}{C} + 2, & if \quad M = G \\ \frac{R-G}{C} + 4, & if \quad M = B \end{cases} \tag{4}$$

where $H = 60° \times H'$

$$I = \frac{R+G+B}{3}, \tag{5}$$

$$S_{HSI} = \begin{cases} 0, & if \quad C = 0 \\ 1 - \frac{m}{I}, & otherwise \end{cases} \tag{6}$$

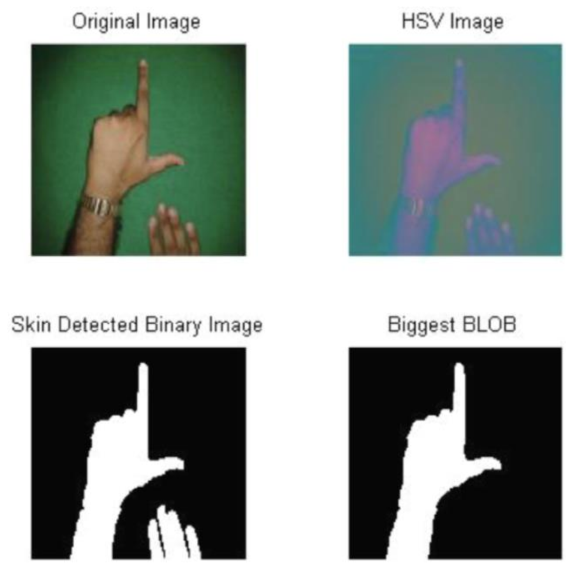

Figure 2 Processing of Skin detection algorithm.

In the preprocessing, filtering and smoothness creates an image, which comprise only the skin colored pixels. There are instances when other objects in the surroundings having almost same pixel values as skin-color like shadows, wood, dress etc., are also evident in the image. The effective skin detection algorithm separates skin color regions using from the non-skin color regions. This image is then accompanied by wrist detection algorithm, discussed below.

Algorithm 1 Skin detection algorithm

1: **procedure** SkinDetection(InputImage, colorModel, SkinToneProjectionProfiles);
/* Comment: This generate *OutputImage* as a binary image where skin pixels ≅ 1 and others ≅ 0 */
2: **begin**
3: **if** (colorModel ~ ‘RGB’) **then**
4: Generate *OutputImage* using skin detection algorithm applying directly to *InputImage* pixels

```
else /* Comment: color models, 'YCbCr ', 'HSL' and 'HSV' undergo same procedure */
Extract the luminance data pixels from the InputImage;
Generate an image with cluster regions of similar pixels using Fuzzy C-Means algorithm;
for all "cluster region" do
Produce projection profiles (PP) for each signal in the input colorModel;
Equate PP with skin tone PP using Distance Correlation (DC);
if (result ≥ threshold value) then assign region as initial skin region, apply region growing (RG) method
end for;
while (cluster of 'initial skin region'≠0) do
Search for 'additional skin regions' from initials using DC and RG;
Implement RGB skin detection on the pixels of 'skin regions' to separate 'real skin regions';
Join clusters of real skin regions' to construct a binary skin OutputImage
endif
end
```

3.2. Wrist detection

The wrist detection algorithm detects and separates hand(s) representing an ISL symbol from an image. The interest here is in the detection hand(s) incorporating wrist involved in forming a symbol. The algorithm proceeds only if there is a presence of hand(s) touching image axes and ignores if a hand is at either of the image diagonals. It finds the wrist in an image considering that a wrist is smaller than a palm of the hand. The algorithm sublimes in approximating the position of the wrist, see Figure 3 and its implementation details are provided below,

Algorithm 2 Wrist detection algorithm

```
procedure WristDetection(InputImage);
  /* Comment: InputImage is the binary image obtained
  after skin detection algorithm */
begin
if (InputImage ~ 'binary') then
Generate OutputImage using wrist detection algorithm applying directly to InputImage regions
else/*Comment: process through skin detection algorithm which undergo the same procedure */
Extract row and column size from the InputImage;
Create separate arrays from horizontal and vertical pixel values;
for all "arrays" do
Find two minimum values of two row arrays;
Find two minimum values of two column arrays;
if (minimum value > 0) then assign minimum value to a variable
else assign pixel value 1, to that variable
end for;
while (minimum value obtained) do
Find the position of two minimum values of two row arrays;
Find the position of two minimum values of two column arrays;
Obtain 4 positions of 4 variables from first and second half of rows and column;
Create an image using "4 variables" wrist detected OuputImage
endif
end
```

3.2.1 Details of the wrist detection algorithm

1) detect wrist from the skin filtered image by scanning from left, right, top, and bottom directions.
2) find the wrist position.
3) find minimum and maximum positions of white pixels.
4) crop image along the coordinates.

Figure 3 Processing of Wrist detection algorithm.

3.3. Feature extraction

A feature is an attribute or property of an object; it is a function of one or more measurements of the object, resulting in a description of the object [24]. When the description of the object is too large, a reduced representation is made in the form of an ordered set of features, also known as feature vector. This transformation of the data to a feature vector is known as feature extraction. In the present case, the object is an ISL symbol image obtained as a result of skin and wrist detection.

Mathematically, the transformation is defined by a set of p-dimensional vectors of weights or loadings $w(k) = (\omega 1, \ldots, \omega p)(k)$ that map each row vector $x(i)$ of x to a new vector of principal component scores $t(i) = (t1, \ldots, tp)(i)$, given by $tk(i) = x(i) \cdot w(k)$ in such a way that the individual variables of t considered over the data set successively inherit the maximum possible variance from x, with each loading vector w constrained to be a unit vector [25]. The first loading vector $w(1)$ thus has to satisfy

$$\mathbf{w}_{(1)} = \underset{\|\mathbf{w}\|=1}{arg\ max} \left\{ \sum_i (t_1)^2_{(i)} \right\} = \underset{\|\mathbf{w}\|=1}{arg\ max} \sum_i (x_{(i)} \cdot \mathbf{w})^2$$

An eigenvector of an image matrix I is a non-zero vector v that, when the image matrix multiplies v, yields a constant multiple of v, the latter multiplier being commonly denoted by λ. That is: $Iv-\lambda v = 0$, (Because this equation uses post-multiplication by v, it describes a right eigenvector.) The number λ is called the eigenvector of I corresponding to v [26].

This generates a one-dimensional vector of length 10,000 columns, since our image dimension is 100 × 100. Such an arrangement ease in vector processing and reduces computational complexity while processing several sets of images.

3.4. Classification

For classification of hand(s) gesture, the proposed system is based on a hybrid approach compositing template matching [27] and Euclidean distance [14] methods. The system proposes to utilize efficient matching of the template images combined with the approximate measures of the distances between test and database images. It is the minimum value of the combination of both minimum of template matching difference and minimum Euclidean distance.

A pixel in the search image with coordinates *(xs, ys)* has intensity *Is(xs, ys)* and a pixel in the template coordinates *(xt,yt)* has intensity *It(xt, yt)*. Thus the absolute difference in the pixel intensities is defined as *Diff(xs,ys,xt,yt)=|Is(xs,ys)−It(xt,yt)|* [28].

$$SAD(x,y) = \sum_{i=0}^{T_{rows}} \sum_{j=0}^{T_{cols}} Diff(x+i, y+j, i, j)$$

The mathematical representation of the idea about looping through the pixels in the search image as we translate the origin of the template at every pixel and take the *SAD* measure is the following:

$$\sum_{x=0}^{S_{rows}} \sum_{y=0}^{S_{cols}} SAD(x,y)$$

Srows and *Scols* denote the rows and columns of the search image and Trows and Tcols denote the rows and columns of the template image, respectively. In this method the lowest *SAD* score gives the estimate for the best position of template within the search image. The method is the simple to implement and understand.

In the testing setup, if $p = (p1,p2)$ and $q = (q1,q2)$ then the distance is given by

$$d(p,q) = \sqrt{(p_1-q_1)^2 + (p_2-q_2)^2}$$

4. EXPERIMENTAL RESULTS

Experimental setup involved a dataset of human hand(s) images for gesture recognition, input to the proposed system. The dataset comprises of human hand(s) images in various lightening conditions in different backgrounds. The proposed system considered 24 alphabets of Indian sign language with 120 samples each, thus a total of 288 images captured using 3.2 & 12 mega pixel camera. The details about the dataset preparation are as follows.

4.1 Database preparation

The proposed system assimilates 24 human hand(s) gestures resembling 24 roman alphabets represented in the ISL symbols. 120 samples of each symbol under different orientations and lightening conditions try to cover every aspects of the challenges faced by hand gesture recognition systems and various approaches. This assembles a database of 288 hand(s) symbols images taken by different individuals available for testing and verification purposes.

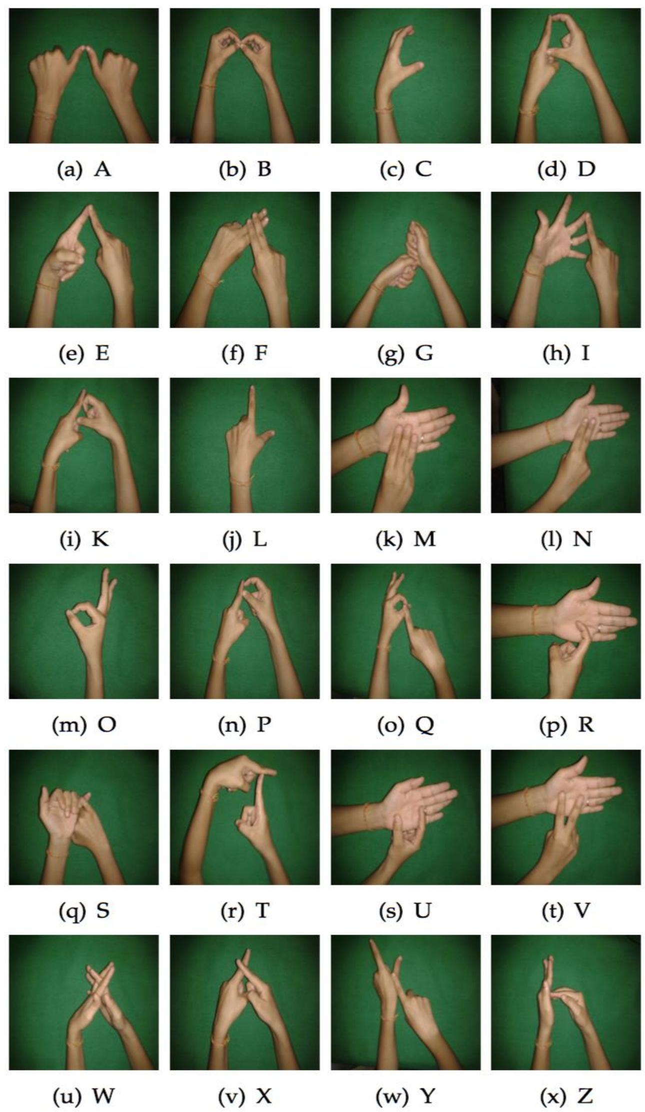

Figure 4 24 signs of the Indian Sign Language.

The setup requires nominal adjustments according to the availability of the subject, more precisely, where the test input is a real-time image or previously stored one. The present system accompanied both alternatives of providing an input, either by real-time imaging equipment or an image stored prior to the system testing.

Symbols	Image samples	Euclidean Distance	Template Matching	Hybrid method
A	120	75	83	96
B	120	50	75	97
C	120	79	83	98
D	120	58	75	94
E	120	65	66	90
F	120	66	67	89
G	120	59	68	87
I	120	58	63	89
K	120	55	66	88
L	120	75	83	98
M	120	50	64	88
N	120	66	65	89
O	120	75	83	99
P	120	81	85	98
Q	120	79	87	99
R	120	58	71	97
S	120	69	62	94
T	120	65	66	91
U	120	50	69	89
V	120	55	61	88
W	120	66	75	94
X	120	58	79	93
Y	120	60	66	95
Z	120	66	75	98
Average	120	**64.08**	**72.37**	**93.25**

Table 1 Recognition accuracy of Euclidean distance, template matching and hybrid approach

Table 1 shows the recognition accuracy of Euclidean distance, template matching and hybrid approaches on the dataset prepared for ISL hand gestures. The hybrid approach sup- presses the individual recognition accuracies of Euclidean distance and template matching. The experiments confirm that the proposed system efficiently recognized different ISL alphabets and eliminating difficulties faced by the methods in the literature. The system takes 8 seconds as an average processing time for an image.

There are some existing challenges in ISL alphabets recognition, since there are both static and dynamic hand(s) gestures. For some of the alphabets there are facial expressions and difference in the hands movement adds to the recognition complexity. Many of the gestures result in obstruction. ISL Involves both global and local hand motions, head and body postures, different hand shapes and hand(s) locations contribute to the sign formation.

5. CONCLUSIONS

This paper presents a human hand(s) gesture recognition system using skin and wrist detection algorithms for ISL recognition. The novelty of the method lies in its skin and wrist detection algorithms, it detects wrist(s) despite of various skin colors. The proposed method uses template matching and Euclidean distance for classification and recognition of hand gestures resembling ISL symbols. The model is tested for 24 static hand(s) gesture signs images with 12 different modalities. The model is being tested for the remaining 2 alphabets ("H" and "J"), since these symbols are dynamically performed. The proposed model achieved an accuracy of 93% correct recognition of hand gestures for ISL interpretation. It is an attempt to overcome the prevailing difficulties in human hand(s) gesture recognition for ISL, generally faced by sensor-enabled hand gloves. Future enhancements would deal with recognition of dynamic gestures in least processing time with improved accuracy.

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Authors

Kavita Yadav is a Teacher in the Secondary level school in Mumbai. She has completed her Masters in Computer Science from University Department of Computer Science, University of Mumbai, Mumbai MH India.

Lalit P. Saxena is a Research Scientist in the Applied Research Section, Combo Consultancy, Obra UP India. He has published over 12 research papers in national and international journals and conferences. He has/is serving as reviewer and technical committee member to various international conferences.

Bilal Ahmed is a PHP developer in Mumbai. He has completed her Masters in Computer Science from University Department of Computer Science, University of Mumbai, Mumbai MH India.

Yugesh K. Krishnan is a Software developer in Mumbai. He has completed her Masters in Computer Science from University Department of Computer Science, University of Mumbai, Mumbai MH India.