A unified framework for the recognition of raised finger in a static hand posture

D.K. Vishwakarma* Sahib Majithia† Nikhil Kumar Mishra‡
Department of Electronics and Communication Engineering,
Delhi Technological University
New Delhi, India
Email: *dvishwakarma@gmail.com ,†sahibmajithia@gmail.com, ‡nkmishra1997@gmail.com

***Abstract*—The main purpose of gesture recognition systems is to understand important expressions of motion by humans which involve hands, head, face, arms, or body.It is of major importance in designing an expert interface between humans and computers.We take into account the two possible fixed geometries to work on. The proposed methods follow the procedure of Preprocessing which helps with noise removal and image enhancement; Segmentation of hand region uses skin likelihood method to extract skin color; Feature extraction uses morphological and geometry based functions to extract the fingers; and active fingers are counted by method of Rule based Classification. In order to test performance, an experiment is conducted using standard and a self-generated dataset of images. The accuracy achieved on these dataset is greater than on similar state of arts.**

Index Terms*—Hand Gestures, Skin Segmentation, Active Fingers, Finger Count, Mask Generation, Recognition, Low Resolution

I. Introduction

An efficient human computer interplay is prominent in the present day framework of interactive and smart computing. Gesture recognition is the leading progress in this direction. Gesture recognition is the substantiated analysis of a human movement by a computing device

There are methods which use extra hardware accessories such as color markers and data glove devices to easily extract a complete classification of gesture traits for identification [1] . Neural Network classifiers have been implemented for gestures classification [2] but it is long-drawn out and as the amount of training data grows, the time necessitated for classification is extended. Orientation histogram method [3] has some inherent difficulties like different gestures could have related orientation histograms, and related gestures might have distinctive orientation histograms. Other methods based on the appearance of the hand use the color of our skin to section the hand and obtain necessary features, these methods are considered natural, simple and less computationally costly compared with methods mentioned before [1] .

Three dimensional hand model based approaches [4] are earning interest in the domain of Gesture Recognition. Three dimensional hand model based approaches are gaining interest in the field of Gesture Recognition. The popular gesture sensors being used presently are:

A. Time-of-Flight Sensors: ToF-based 3D hand gesture recognition system uses point gestures to control a robot [5].

B. Kinect
1) skeletonbased recognition [6] and
2) depth-based recognition.

C. Leap Motion: Leap Motion is a newly released sensor that focuses on the accurate 3D hand positioning. It concentrates on a specific region and has gained prevalence over Kinect sensor concerning better accuracy [7].

This paper proposes two methods for counting the number of active fingers. These are proposed based on the geometric facts of the hand region.

Since the proposed method works on geometric properties and does not require any extracted features; it works well on low-resolution images which is a great advantage for developers regarding data storage.

The algorithm first helps with skin segmentation from the region of interest. Further, the number of active fingers are counted after operating them with a range of morphological operations. In this paper section II and III and IV describe the algorithms proposed. Further sections discuss the Results (V), Conclusion and Future scope (VI) of our work.

II. Hand Segmentation

Skin segmentation obtains the hand region. The skin segmentation has been applied correctly to Region of Interest of hand region. This does not cause susceptibility as the Region of Interest can be easily extracted by different depth estimation strategies, which include:

Active methods: Light-based depth estimation/Pattern projection/Ultrasounds based methods

Passive methods: Monocular depth estimation/Image structure/Points tracking or Optical flow/ Multiview solutions for the depth estimation

The Region of interest can also be extracted by using instruments like Kinect which uses an RGB camera with a depth sensor.

We have used gestures G1, G2, G3, G4 and G5 which are shown with their respective extracted Region of Interest.

A. *SKIN SEGMENTATION*

The most important part of hand gesture recognition is the skin segmentation. Segmentation accuracy determines the eventual success or failure of an automated analysis procedure.For segmentation, we first convert the RGB colored image into the YCbCr color model.

(a) G1 (b) G2 (c) G3 (d) G4 (e) G5

Fig. 1: Gestures used with extracted ROI

The transformation of the original RGB colour image is done using the equations (1),(2) and (3):

$$Y = 0.2990R + 0.5870G + 0.1140B \tag{1}$$

$$Cb = -0.1687R - 0.3313G + 0.5000B \tag{2}$$

$$Cr = 0.5000R - 0.4187G - 0.0813B \tag{3}$$

The mean values of chrominance components are used to extract the skin color of the hand by dropping the luminance component because the variation in skin color is more in intensity than in chrominance. In YCbCr color space, the components Cb and Cr represent the chrominance and component Y accounts for the luminance.

In the earlier works, the YCbCr color model has been used by a basic mathematic operation of thresholding on chromaticity and luminance values. No method has yet been settled which determines the thresholding accurately.So, alternatively, we use a modified approach called a skin likelihood model for skin segmentation.

This model is devised from the maximum likelihood paradigm, which has two parameters: covariance matrix and mean vector that maximizes the likelihood function. The Gaussian likelihood function [8] has unique maxima, and the parameters covariance matrix (Υ) and mean vector(ξ) are calculated as:

$$\Upsilon_i = \frac{1}{n}\sum_{k=1}^{\infty} y_k \tag{4}$$

Where i $\in$ {Cb,Cr} Cb and Cr are the values of chrominance in YCbCr color space.

$$\xi = \frac{1}{n}\sum_{k=1}^{\infty} (y_k - \Upsilon)(y_k - \Upsilon)^T \tag{5}$$

The probability distribution of skin class can be written as:

$$p(\frac{y}{skin}) = g(y, \Upsilon, \xi) \tag{6}$$

$$g(y, \Upsilon, \xi) = \frac{1}{(2\pi)^{\frac{d}{2}}\left(det\left(\xi\right)\right)^{\frac{1}{2}}} \times exp(-\frac{1}{2}\delta^2) \tag{7}$$

Where d is the dimension of the feature vector, and $\delta^2 = (y - \Upsilon_i)\xi^{-1}(y - \Upsilon_i)^T$ .From equation (7), the pixels can be classified as skin and non-skin color pixels by using the decision boundary. The probability density distribution of the formed Gaussian model is represented in Fig.2 :

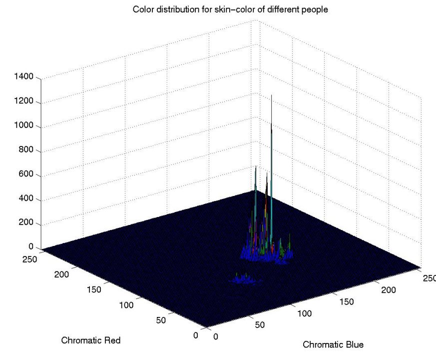


Fig. 2: Graph describing variation of skin tones of human race in Chromatic colour model

Plotting a Gaussian Curve for this variation yields the Graph in Fig 3.

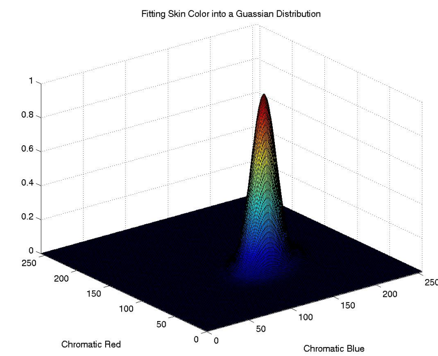


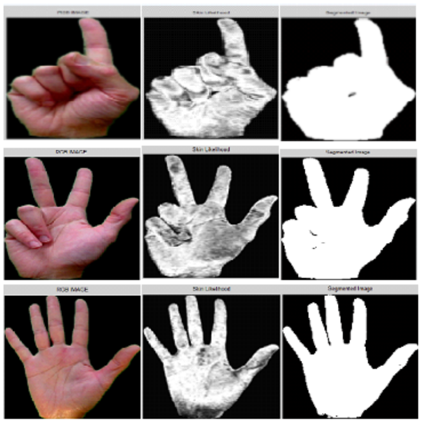
Fig. 3: Gaussian curve of variations in Fig.1

This Method has a great accuracy and calibration advantage over the YCbCr model and is thus more user-friendly. It can be calibrated for all fairer to darker skins with just a change in input skin segment (which was calibrated with the Gaussian); in contrast to change in Cb and Cr values which demand a technical blueprint.

B. PSEUDO CODE:

$imresize([200\ \ x\ \ 200])$
SKIN SEGMENTATION:
$Calibrate\, skin\, model$:
$function\, outputs[mean(cr), mean(cb), cov(cr, cb)]$
$x = [(cr - r_{mean}); (cb - b_{mean})];$
$likely\_skin(i, j) = [power(2 * pi * power(det(rbcov), 0.5), -1)] * exp(-0.5 * y' * inv(rbcov) * y);$
For every pixel we calculate :
$likely\_skin(i, j) = [power(2 * pi * power(det(rbcov), 0.5), -1)] * exp(-0.5 * y' * inv(rbcov) * y);$
% gives the Gaussian of the image.
$BW = im2bw(likely_s kin, thresh);$ % Morphological operations for segmenting the hand shape accurately

$a = imclose(BW)$;
$b = imdilate(a)$;
$c = imfill('holes')$;
Find the hand(palm) width.



III. PROPOSED METHODS

A. Method 1: MASKING APPROACH

After acquiring a binary image of the segmented skin region, we extract the count of active fingers by a distinct system of morphological operations.

1) MORPHOLOGY: Morphology is a comprehensive collection of image processing methods that process images by shapes and contours.

Dilation and Erosion work (at least conceptually) by translating the structuring element to various points in the input image, and examining the projection between the translated kernel coordinates and the input image coordinates.

Mathematically, the main morphological operations we use are denoted as follows:

a) EROSION:

$$(J \ominus K) = [z|(K)_z \subseteq J] \tag{8}$$

b) DILATION:

$$(J \oplus K) = \left[z|(\widehat{K})_z \cap J \neq \phi\right] \tag{9}$$

imopen:

$$(J \;\; o \;\; K) = [(J \ominus K) \oplus K] \tag{10}$$

imclose:

$$(J \cdot K) = [(J \oplus K) \ominus K] \tag{11}$$

2) OPERATIONS: The palm width calculation is needed for obtaining the finger width.

The finger width lies between 1/3 to 1/4 times the palm width depending on the stretch of fingers.

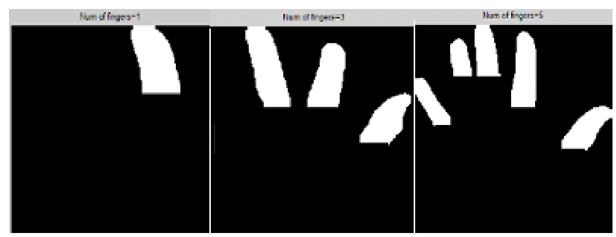
An erosion filter is then designed which is of the dimension of the finger girth. This filter is employed for erosion on the binary segmented image. Dilation of this image helps obtain the mask (here palm).

Morphological opening, closing, and other fitting operations should be executed to accomplish a noise-free and an explicitly shaped mask.

The subtraction of the mask [9] from the binary image provides us the active fingers of the image. Further thresholding for the area of the acquired portions presents us with the precise count of active fingers.

3) PSEUDO CODE: **Masking Approach**

3 <ratio <4
$erode\_filter = ones(1, floor(width/ratio)$; % remove small components such as noises and uneroded finger parts
$bwareaopen(eroded\_image, 40)$; %dilate to obtain the original palm shape and size.
$fingers = \; palm. * BW$
$regionprops \rightarrow$ Area threshholding to count the no. of bounding box to count the number of fingers.



B. Method 2: GRADIENT APPROACH

After acquiring a binary image of the segmented skin region, we extract the count of active fingers by using the information of the change of gradients at the finger-tip region.Once the centroid of the binary image is acquired, we determine the shortest distance to the boundary of the silhoutte from the centroid point. This minimum distance is defined in all directions from the centroid.The area hereafter produced showcases the mask for the binary silhouette.It comprises the palm region of the hand and thus forms the base of the mask [10].Mask subtraction then gives us the fingertip section in addition to the wrist area.

Gradients are calculated by using filters :
Gx: forward horizontal difference
Gy: forward vertical difference

$$Gradient = \sqrt{G_x^2 + G_y^2} \tag{12}$$

We use sobel gradient operator for our method.

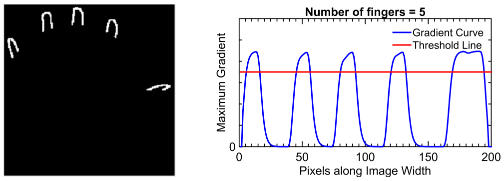
$$\begin{array}{cc} G\text{x} & G\text{y} \\ \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix} & \begin{bmatrix} -1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \end{array}$$

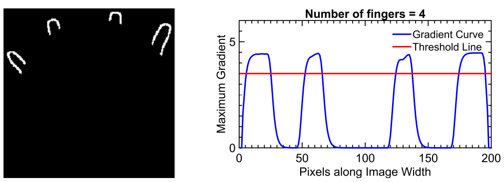
Gradient map of the obtained image is calculated. The geometry of the hand infers that the wrist area has a small change of slope at the boundary region though the change is high for the fingertips.

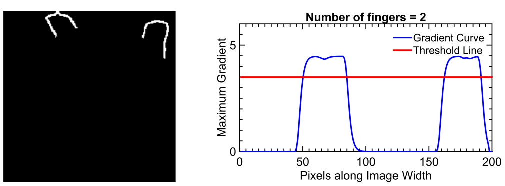
Thus a suitable threshold is established to segregate the wrist area.

The gradient map is transferred via a low-pass filter to eliminate the noise effects. The low-pass filter also helps identify the false high-gradient-change locations.

The final gradient map is a plot for column locations, and thresholding identifies the count of fingers.







1) *PSEUDO CODE:* **Gradient Approach**

$erode\_filter = strel('disk', 5)$; % remove small components such as noises and uneroded finger parts
$[Gmag, Gdir] = imgradient(eroded\_image)$; % find the change and direction of gradient at the boundary of the entire hand region.
for $i = 1 : width$
  for $j = 1 : length$
    $D = [i, j; x\ co - ordinate\, of\, centroid, y\ co - ordinate\, of\, centroid]$;
    $d = pdist(\mathrm{D})$; % find the Euclidean Distance between every boundary point from the centroid.
    $Dist(j, i) = d$; % distance matrix.
Low pass filter $\rightarrow$ Removes the noise effects, identifies the false high-gradient-change locations.
Plot the final gradient map $\rightarrow$ column locations, and thresholding identifies the count of fingers.

IV. RESULT

The rule-based classifiers learned model is represented as a set of if-then rules. Let the correct number of tests be c out of a total of t tests. Accuracy is then given by $(c/t) * 100$.

(a) G1 (b) G2 (c) G3 (d) G4 (e) G5

Fig. 4: Hand Gestures used from Standard Database

A. *STANDARD DATA-SET*

We applied our algorithms on standard Massey University database [11] of images available online.We used only 5 hand gestures from the data-set. The skin segments taken to train our Gaussian skin model were randomly taken from the people of the same ethnicity as that of the dataset.

Accuracy by Masking Approach: - 93.622%

Accuracy by Gradient Approach: - 90.136%

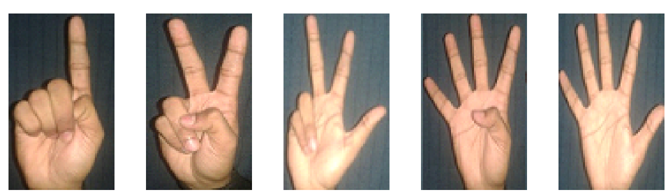
TABLE I: Confusion Matrix for Masking Approach

	Predicted Class				
Actual Class	G1	G2	G3	G4	G5
G1	0.9275	0.0725	0	0	0
G2	0	1	0	0	0
G3	0	0	0.92	0.08	0
G4	0	0	0.014	0.972	0.014
G5	0	0	0	0.0923	0.8616

TABLE II: Confusion Matrix for Gradient Approach

	Predicted Class				
Actual Class	G1	G2	G3	G4	G5
G1	0.884	0.116	0	0	0
G2	0.0143	0.9429	0.0428	0	0
G3	0.0133	0.12	0.8534	0.0133	0
G4	0.014	0.014	0.07	0.888	0.014
G5	0	0	0	0.0615	0.9385

B. *OUR DATA-SET*



(a) G1 (b) G2 (c) G3 (d) G4 (e) G5

Fig. 5: Hand Gestures used from our created dataset

To have an understanding of real time results, we collect our database of images and further test the accuracy. Ten pictures of ten different individuals were taken. The skin segments taken to train our Gaussian skin model were randomly taken from the skin samples of people of various ethnicity and region like North Indians, South Indians, North East Indians to test the robustness of our algorithm.

Accuracy by Masking Approach : - 96%

Accuracy by Gradient Approach : - 98%

TABLE III: Confusion Matrix for Masking Approach

	Predicted Class				
Actual Class	G1	G2	G3	G4	G5
G1	1	0	0	0	0
G2	0	0.9	0.1	0	0
G3	0	0	1	0	0
G4	0	0	0	1	0
G5	0	0	0	0.3	0.7

TABLE IV: Confusion Matrix for Gradient Approach

	Predicted Class				
Actual Class	G1	G2	G3	G4	G5
G1	1	0	0	0	0
G2	0	1	0	0	0
G3	0	0	1	0	0
G4	0	0	0	1	0
G5	0	0	0	0.3	0.7

TABLE V: Comparison of various methods

Method for feature extraction and classifier used	Average Accuracy
Bayes classifier [12]	83.40%
PCA	72.73%
Kumar's Autoencoders [13]	83.36%
Masking Approach	93.62%
Gradient Approach	90.13%

V. Conclusion and Future Scope

This paper deals with two algorithms to understand the hand gestures and also compares their performances with each other as well as established methods [14]. In our work, we use the geometry of the hand for the recognition of hand gesture. It is a traditional type of algorithm and is thus robust.The proposed methods do not need any training phase [15] to classify the hand gestures so is better than neural networks.

Sign Language Recognition, Robot Control automation of home appliances and presentation control are few of many applications of hand gesture recognition systems. Usage of hand gestures can be extended to control real time applications like pdf reader, VLC media player, paint, and so forth. This wireless control of embedded instruments is a significant progress towards the field of embedded vision and automation.

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