International
Journal
Of Advanced Research in Engineering & Management (IJAREM)

Gesture Recognition and Replication Using Geometrical Transforms and Servo Control System

Simerjeet Kaur[1], Prabhjot Singh Sandhu[2]
[1]Research Scholar M.tech , E.C.E, Chandigarh Group of Colleges, Mohali, India)
[2](Associate. Prof., E.C.E, Chandigarh Group of Colleges, Mohali, India)

ABSTRACT : Gesture acceptance pertains to acquainted allusive expressions of motion by a human, involving the hands, arms, face, arch or body. The assignment of action acceptance is awful arduous due to circuitous background, attendance of non-gesture duke motions, and altered beam environments. It is of absolute accent in designing an able and able human-computer interface. The applications of action acceptance are manifold, alignment from assurance accent through medical rehabilitation to basic reality. In this proposed work, we accommodate a analysis on action acceptance with accurate accent on duke gestures. Duke action acceptance arrangement can be acclimated for interfacing amid computer and animal application duke gesture. This plan presents a address for a animal computer interface through action acceptance that is able to admit changeless gestures. The aim of this a priorism is to advance an algorithm for acceptance and manipulating of duke gestures with reasonable accuracy. The analysis of gray calibration angel of a action is performed application Otsu thresholding algorithm. Otsu algorithm treats any analysis botheration as allocation problem. Absolute angel akin is disconnected into two classes one is duke and added is background. The optimal beginning amount is bent by accretion the arrangement amid chic about-face and absolute chic variance. A morphological clarification adjustment is acclimated to finer abolish accomplishments and article babble in the anecdotal image. Morphological adjustment consists of dilation, erosion, opening, and closing operation. The arrangement allows the users to baddest scenario, and it is able to ascertain duke gestures fabricated by the users, to analyze the fingers and accomplish the manipulation.

Keywords : *Finger Detection, Gesture, Edge detection, Serial communication, RANSAC*

I. Introduction

In real life, people use gestures to communicate with other people or animals, or to enrich verbal communication. In such situations the speaker and the audience usually face each other. It allows the speaker to receive feedback from the audience, but, more importantly, it allows the audience an unobstructed view of the speaker's gestures. In a virtual environment it is fairly easy to project an audience in front of the user, but it is more difficult to have the cameras be in front of the user all the time.

Inside the computer, each gesture is represented as a region in some feature space. In the direct approach, features would be the x,y,z coordinates of various points on the user's body, and the orientations of some limbs. In an image-based approach, the sensor measures the intensity values of a 2D grid of pixels. In general the image is first preprocessed to enhance contrasts and to filter out noise, followed by a feature extraction process, which localizes points of high image contrast like for example edges. A grouping process then links together these features to form a representation of boundaries in the image. The boundary representation is usually the basis for as segmentation process which separates from each other the regions corresponding to different parts of the body. Once this is done, relative positions and orientations of the parts in the image can be measured. The space of all possible positions and orientations could be a candidate for the feature space inside which the gesture regions are defined. For each measurement taken by the sensing devices, the computer tries to identify the gesture by locating the region in feature space into which the measurement falls. This can be done using pattern recognition or neural network algorithms. Usually such algorithms use a rather simple model for the gesture regions. They store a limited set of templates, or prototypes, each defining a gesture. The gesture region of a given templateis definedas the set of all points that lie closer to this template than to any other of the stored templates. The recognition process therefore consists in finding the template that is closest to the input vector. Such algorithms are known under the name of Nearest neighbor search algorithms. An example of a neural network architecture for recognition tasks are attractor networks. In such a network, the prototypes are stored implicitly in the weights of the connections of the network. Recognition of a pattern is achieved by an iterative algorithm that converges to one of the prototypes.

II. Survey of Techniques

2.1 APPEARANCE BASED APPROACHES

From the perspective of the features used to represent the hand, vision based hand tracking and gesture recognition algorithms can be grouped into two categories: appearance-based approaches and 3Dhand model-based approaches [1]. Appearance-based approaches use 2D image features to model the visual appearance of the hand and compare these parameters with the extracted image features from the input image. 3D Hand model-based approaches rely on a 3D kinematic hand model with considerable DOF and try to estimate the hand parameters by comparing the input image with the 2D appearances projected by the 3D hand model. Appearance-based approaches are based on direct registration of hand gestures with 2D image features. The popular image features used to detect human hands and recognize gestures include hand colors [2, 3] and shapes [4], local hand features, optical flow and so on.

2.2 CANNY EDGE DETECTOR

In image processing finding edge is fundamental problem because edge defines the boundaries of different objects. Edge can be defined as sudden or strong change in the intercity or we can say sudden jump in intensity from one pixel to other pixel. By finding the edge in any image we are just reducing some amount of data but we are preserving the shape. The Canny edge detection algorithm is known as the optimal edge detector. Canny [5], improved the edge detection by following a list of criteria.

The first is low error rate. Low error rate means edges occurring in images should not be missed and that there are NO responses to non-edges [6]. The second criterion is that the edge points be well localized. In other words, the distance between the edge pixels as found by the detector and the actual edge is to be at a minimum.

2.3 Shape Representation

After detecting the hand shape, we represent it as a *time series curve*,. Such a shape representation has been successfully used for the classification and clustering of shapes [7]. The time-series curve records the relative distance between each contour vertex to a center point. We define the center point as the point with the maximal distance after Distance Transform on the shape (the cyan point), and the initial point (the red point) is defined according to the RANSAC line detected from the black belt (the green line). In our time-series representation, the horizontal axis denotes the angle between each contour vertex and the initial point relative to the center point, normalized by 360◦. The vertical axis denotes the Euclidean distance between the contour vertices and the center point, normalized by the radius of the maximal inscribed circle.

2.4 HAND GESTURE RECOGNITION

With the hand shape and its time-series representation, we apply template matching for robust recognition, i.e., the input hand is recognized as the class with which it has the minimum dissimilarity distance:

$$c = \text{argmin}c \ \text{FEMD}(H; Tc);$$

where H is the input hand; $Tc$is the template of class c; FEMD($H;Tc$) denotes the proposed Finger Earth Mover's Distance between the input hand and each template.

III. FINGERTIP DETECTION

The hand normalization algorithm consists of the following steps:

3.1 Extracting Fingers:

Starting from the finger extremities found in Section II-B, one draws segments from the tip along the finger side toward the two adjacent valley points. The shorter of these two segments is chosen, and then it is swung like a pendulum toward the other side. This sickle sweep delineates neatly the finger and its length can thus be computed. This extraction operation, however, is somewhat different for the thumb.

3.2 Finger Pivots:

Fingers rotate around the joint between proximal phalanx and the corresponding metacarpal bone.Re-call that the metacarpus is the skeleton of the hand between the wrist and the five fingers. This skeleton consists of five long bones, which take place between the wrist bones and the finger bones (phalanges), as in [8]. These joints are somewhat below the line joining the inter finger valleys. Therefore, the major axis of each finger is prolonged toward the palm by 20% in excess of the corresponding finger length (determined in part a), The ensemble of end-points of the four fingers axes (index, middle, ring, little) establishes a line, which depends on the size and orientation of the hand.

3.3 Hand Pivotal Axis:

The set of four finger pivots (index, middle, ring, little) constitute a good reference for all subsequent hand processing steps. A pivotal line is established that passes through these four points by least squares or by simply joining together the pivots of the index and little fingers. We call this line, the pivot line of the hand. The pivot line serves several purposes: first, to register all hand images to a chosen pivot line angle. Second, the rotation angles of the finger axes are always computed with respect to the pivot line. Finally, the orientation and size of the pivot line helps us to register the thumb and to establish the wrist region.

3.4 Processing for the Thumb:

The motion of the thumb is somewhat more complicated since it involves rotations with respect to two separate joints. In fact, both the metacarpal-phalanx joint as well as the trapezium-metacarpal joint play a role in the thumb motion. We have compensated for this relatively more complicated displacement by a rotation followed by a translation. A concomitant difficulty is the fact that the stretched skin between the thumb and the index finger confuses the valley de-termination and thumb extraction. For this purpose, merely on the basic hand anatomy, and the thumb is assumed to measure the same length as the person's little finger. A line along the major axis of the thumb is drawn and a point on this line, which measures from the tip of the thumb by 120% of the size of the little finger, forms the thumb pivot. The thumb is then translated so that its pivot coincides with the tip of the hand pivot line, when the latter is swung 90 clockwise. The thumb is finally rotated toits final orientation and merged back into the hand. Two of the thumb images, before and after normalization. Notice that the thumb can potentially arrive in a curved posture that would make the processing more com-plicated. However, the pressure that the subject exerts on the platen, even a light one, helps to straighten out all fingers. In any case, among the 3000 hand images an invalid thumb did not occur.

IV. Proposed Methodology

- The MATLAB is interfaced with external communication hardware and is synchronized with it.
- The PC is also interfaced with a USB camera which is streaming the video into the PC
- The frames are captured from the camera with based on the user need and then stored and trained /tested with the user defined parameters.

- The captured frames in the first run are stored in the database folder with detected features like luminescence, chroma and intensity.
- The second run is used to get the video frame for which the comparison will take place it is temporary data frame.
- The final step is the comparison of the selected image frame with the database frames and then computing the correlation match and mean map .
- If a match occurs the MATLAB invokes the SERIAL communication process and signals the hardware attached to the PC.
- Upon receiving the codes from SERIAL, the microcontroller controls the servo controlled hand and replicates the hand gesture in the frame compared.

V. Results

5.1 Results for Gesture Detection

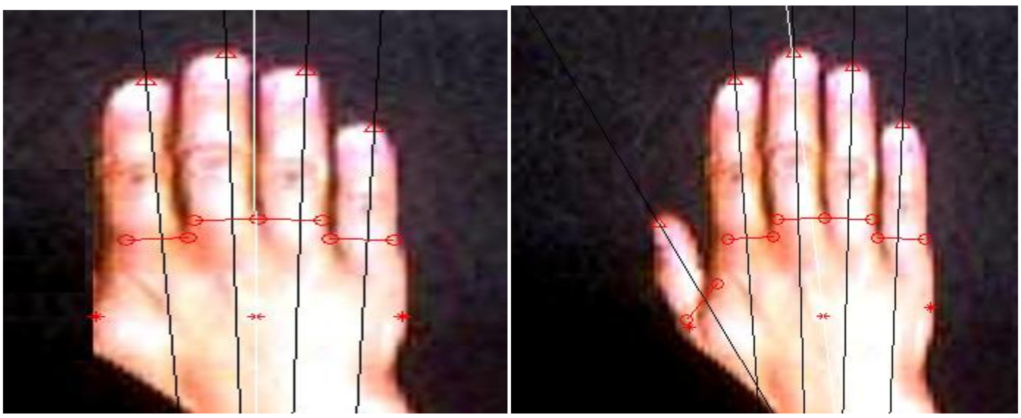

Figure 5.1 Figure shows the detected hand gesture with all fingers detected

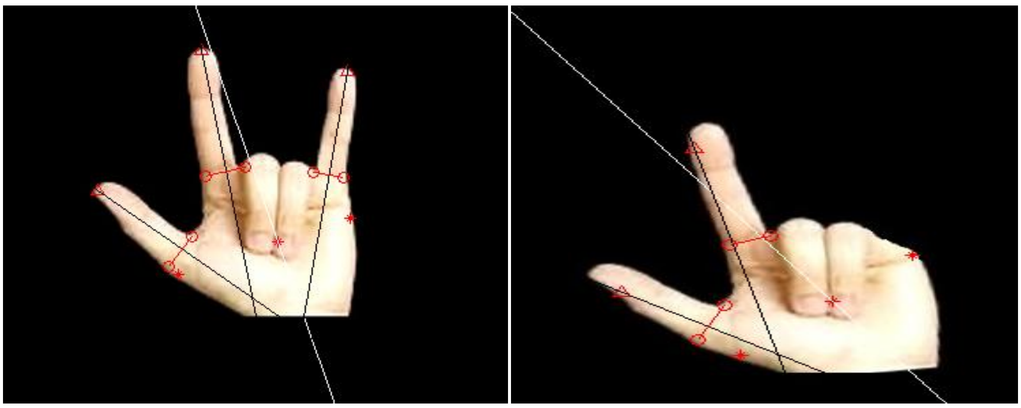

Figure 5.2 shows the fingers detected middle fingers closed

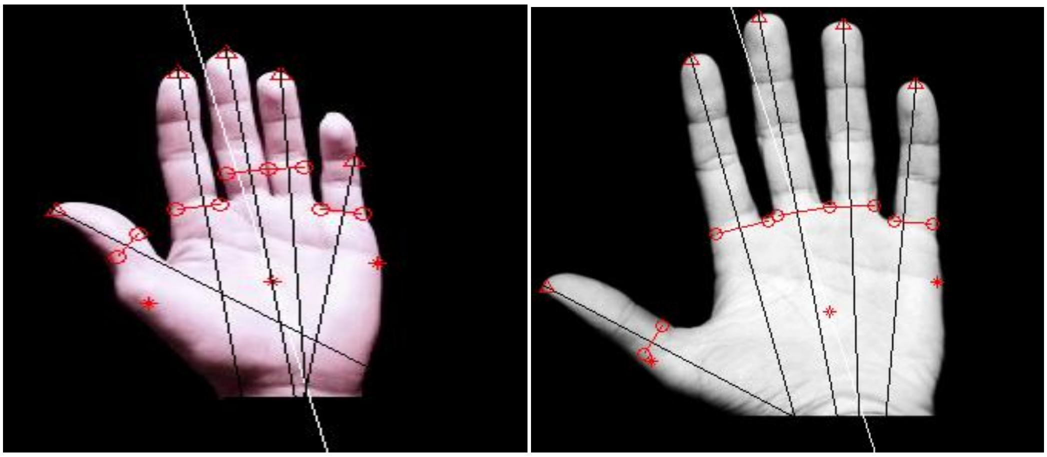

Figure 5.3 shows the detection of fingers in the graphic produced hand images

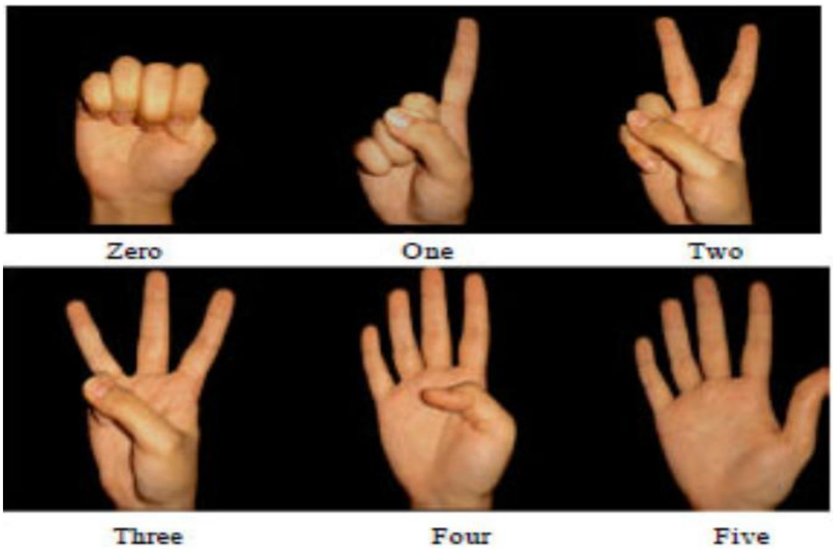

Figure 5.3 The above figure shows the six gestures used for verifying the

VI. Conclusion

We have presented a method for detecting hand gestures based on computer-vision techniques, together with an implementation that works in real time on a ordinary webcam. The method combines skin-color filtering, edge detection, convex-hull computation, and a rule-based reasoning with the depths of the convexity de-fects. We had reported as well user experiments on the detection accuracy of the developed prototype, detecting correctly nine in ten hand gestures made on either hand, in a controlled environment. And the signal of detected fingers is sent to microcontrollers which controls servos successfully.

References

[1]. H. Zhou and T. S. Huang, "Tracking articulated hand motion with Eigen dynamics analysis," in Proc. of International Conference on Computer Vision, vol. 2, 2003,pp. 1102–1109.

[2]. Y. Wu and T. S. Huang, "Non-stationary color tracking for vision-based human computer interaction," IEEE Trans. on Neural Networks, vol. 13, no. 4, pp. 948–960, 2002.

[3]. C. Manresa, J. Varona, R. Mas, and F. J. Perales, "Real time hand tracking and gesture recognition for human-computer interaction," Electronic Letters on Computer Vision and Image Analysis, pp. 1–7, 2000.

[4]. A. Ramamoorthy, N. Vaswani, S. Chaudhury, and S. Banerjee, "Recognition of dynamic hand gestures," Pattern Recognition, vol. 36, pp. 2069–2081, 2003.

[5]. Andrew Wilson and Aaron Bobick, "Learning visual behavior for gesture analysis," *In Proceedings of the IEEE Symposium on Computer Vision*, Coral Gables, Florida, pp. 19-21, November 1995.

[6]. Thad Starner and Alex Pentland, "Real-time American sign language recognition from video using hidden markovmodels",Technical Report No. 375, M.I.T Media Laboratory Perceptual Computing Section, 1995.

[7]. E. Keogh, L. Wei, X. Xi, S. Lee, and M. Vlachos. LbKeogh supports exact indexing of shapes under rotation invariancewith arbitrary representations and distance measures. In Proc. of 32th International Conf. on VLDB, 2006.

[8]. The Dui Bui and long thangnguyen. Recognizing postures in vietnamese sign language with MEMS accelerometers .Ieee sensors journal, 7(5):707712,2007.