1-1-2013

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Keywords

recognition, gesture, overview, hand

Disciplines

Engineering | Science and Technology Studies

Publication Details

S. Yang, P. K. Premaratne & P. J. Vial, "Hand gesture recognition: An overview," in 5th IEEE International Conference on Broadband Network and Multimedia Technology (IC-BNMT 2013), 2013, pp. 63-69.

Hand Gesture Recognition: An Overview

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Abstract

Hand gesture recognition has been applied to many fields in recent years, especially in man-machine interaction (MMI) area, which is regarded as a more natural and flexible input. In this paper, an overview of hand gesture recognition research up to date is presented, which includes common stages of hand gesture recognition, common methods and technique of each stage, the state of the recent research and summaries of some successful hand gesture recognition models.

Keywords: Hand Gesture Recognition, Man- Machine Interaction (MMI), Segmentation, Feature Extraction, Gestures Recognition, Neural Network

1. Introduction

With the development of man-machine interaction (MMI) in recent years, new control and input technologies of MMI are becoming ubiquitous, especially gesture recognition. Compared with keyboard and mice, physical gesture is considered as a natural, easy and attractive command for MMI. But people who have different cultural backgrounds cannot easily have a common view on gestures, a simple definition of the term gesture is "a motion of the body that conveys information" [1]. Gesture recognition has been researched for over two decades and there are various applications of gesture recognition for different purposes such as robot control [2], sign language recognition [3], graphic editor control [4], virtual environment [5], television control [6], 3D modeling [7] etc.

In the field of hand gesture recognition research, the hand gesture should be defined as a gesture or a posture which resulted from the movement of a combination of hand and arm [8]. Although the hand gesture and hand posture has a similar meaning in daily life, there are some differences. Hand gesture means a dynamic movement such as sign languages and waving hands which is complex but suitable for a real time environment. Mitra defined three elements for a gesture, finger movement, wrist movement and hand position and orientation changes [9]. Hand posture always means static and certain pose, such as thumbs up, pointing and a victory sign, which requires less computational complexity [1].

2. Non-vision based hand gesture recognition

According to different approaches of acquiring hand gesture information, hand gesture recognition can be divided into two groups; one is non-vision based recognition, such as data gloves, and another is vision based recognition. As hand is a deformable object, it cannot be represented by one simple model, besides, human hand tracking and recognition are easily influenced by environment factors such as, luminance, colour and so on, so many previous research are about non-vision based recognition, especially on data glove devices [10][11].

Fig.1 One typical data glove called Immersion CyberGrasp [39]

Data glove (Shown in Fig. 1) is a multi-function Virtual-Reality (VR) device comprising of many sensors on the glove. Through software mapping, the glove can "reach into the computer" to move, clutch and rotate the virtual objects. The latest release of this product is capable of registering finger bends for each finger. The glove accurately transmits hand gesture to the computer in real time, and then receives feedback from virtual environment to the operator. It provides the user a direct and universal human-computer interaction mode [11].

Ruize Xu et al. [5] proposed a method based on data glove theory using a contact type sensor, MEMS 3-axes accelerometer to recognize seven hand gestures which includes up, down, left, right, tick, circle and cross. The hand motions are captured by the accelerometer in three vertical directions and then the data were transferred to a computer via Bluetooth. Before features extraction process, the system will segment the hand gesture from the input data. Because of the complexity of the gestures from different people, an 8 digit sign sequence is extracted as common features using the accelerometer. The system recognizes gestures by comparing the templates in the data base. This method has two constraints; one is this system requires people to wear sensors sacrificing natural feeling of hand gestures; another is that this system strikes a balance between accuracy and number of gestures by resorting to only seven gestures. Because it is only based on the MEMS accelerometers, the accuracy is acceptable when the database is small. If this system is trained on more hand gestures, the accuracy would decrease due to erroneous classification. The experiment shows the recognition rate of this model is 95.6%, the recognition of each gesture range from 91%-100%.

3.Vision based hand gesture recognition

In recent years, more and more research has concentrated on vision based hand gesture recognition. Compared to non-vision based recognition (data glove or electro-magnetic waves etc.), vision based recognition are more natural and comfortable for the user [12] as contact type devices reduces the flexibility of hand movements. Based on the data glove and electromagnetic waves, researchers developed a new kind of colour glove (also called colour makers) (Fig.2) [12][13] and one non-contact optical sensor chip used for hand gesture recognition.

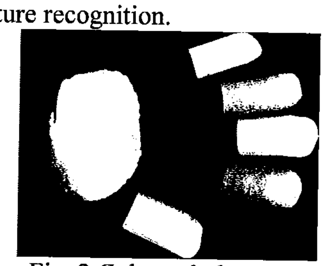

Fig. 2 Coloured glove [13]

3.1 Computer vision based hand gesture recognition

Getting a computer to accurately interpret a human hand gesture or posture is a non-trivial task. With the rapid development of computer hardware, the computational ability of a computer has achieved tremendous growth over the last decade. This has facilitated a computer to be used for HCI giving people freedom to naturally and flexibly input information. In the latest research, computer vision-based hand gesture recognition plays a very important role in the human computer interaction (HCI) area.

A computer vision-based hand gesture recognition system can be divided into four parts (Fig.3). First stage uses one or multiple cameras to obtain image data, and then according to the data model, check the input data stream if it has hand gesture information. Once the computer detects that a hand gesture is present, segmentation is used to derive the posture only removing any background. This is then used for feature extraction stage which will be used for classification as the final goal of the process. During the identification or classification stage, according to parameters of the model, system classifies the received hand gestures to generate hand gesture description. Finally, based on the description, the system drives the specific application [14, 15].

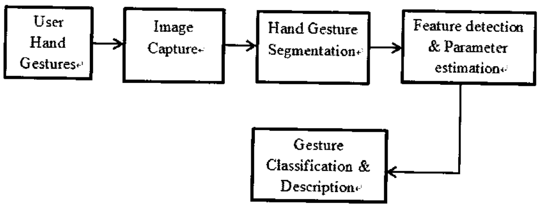

Fig. 3 Stages of vision based gesture recognition system.

3.1.1 Image segmentation

Image segmentation is the first step of hand gesture recognition; it aims to isolate the hand gesture from the input image. The segmentation methods are mainly depended on skin colour detection or grey scale (colour or depth) information. It has been very well established that skin segmentation can be better performed on HSV or YCrCb colour space [16].

3.1.1.1 HSV (Hue, Saturation, Value)

To specify the parameter of colour image, HSV colour space is introduced. Hue refers to different colours (such as red, green), S refers to saturation (for instance, the difference between deep blue and light blue), and V refers to value (also considered as brightness) [16]. To represent the image accurately with intuitive values, HSV colour space was widely used for image segmentation. Assume the (r, g, b) are the coordinates of red, green and blue respectively. The values are from 0 to 1. Max represents the maximum value among r, g and b. Min represents the minimum value among the r, g and b. The h means the hue angle (between 0-360), S means the saturation, and then these parameters can be calculated as follows. [17][18]

$$h=\begin{cases} 60*\dfrac{g-b}{max-min}+0 & if\ max=r\ and\ g\geq b \\ 60*\dfrac{g-b}{max-min}+360 & if\ max=r\ and\ g<b \\ 60*\dfrac{b-r}{max-min}+120 & if\ max=g \\ 60*\dfrac{r-g}{max-min}+240 & if\ max=b \end{cases} \quad (1)$$

$$s=\begin{cases} \dfrac{\max-\min}{\max}=1-\dfrac{\min}{\max} & otherwise \\ 0, & if\ \max=0 \end{cases} \quad (2)$$

$$v=max \quad (3)$$

Mokhtar M. Hasan et al. [16] proposed a new system to achieve higher segmentation accuracy rate, which is based on HSV colour space method. This system divided the input image into blocks to extract features. The basic concept is to find the proper block number to achieve the high performance of segmentation rate. They considered all blocks from 1x1 up to 23x23 block size.

3.1.1.2YCbCr

YCbCr is also a widely used colour space method during image segmentation. Y represents luminance. Cb and Cr represent blue-difference and red-difference chroma components respectively. RGB values can be transformed to YCbCr colour space as follows. [17]

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix}=\begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix}+\begin{bmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112 \\ 112 & -93.786 & -18.214 \end{bmatrix}\begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (4)$$

Shuying Zhao et al. [19] proposed an improved algorithm of hand gesture recognition for intricate background. This paper illustrates the segmentation method based on YCbCr colour space, and also compared four segmentation methods, HSV, YCbCr, Nrg_r and Nrg_g. Then authors built a model using Gaussian distribution. This model is highly capable of rejecting the effect of near-skin colour objects.

3.1.1.3 Skin colour detection

The skin colour detection techniques are common based on threshold technique. According to different areas the threshold value applied, the segmentation method can be divided into two groups, one is the threshold value only used in one region and the other is the threshold value used in the whole image [20].

The threshold value is used to classify the points which have similar features on the image into the same class. Assume input image is $f(x, y)$, the output is $f'(x, y)$, the threshold is T, the segmentation process using threshold can be described as following formula: [21]

$$f'(x,y)=\begin{cases} a_1 & f(x,y)<T \\ a_2 & f(x,y)\geq T \end{cases} \quad (5).$$

The threshold-based segmentation process finally produces two value images. The features of the image is usually the colour, grey scale or other (X factor, such as, one particular characteristic) information of the image. Assume the threshold is described as follow:

$$T(\ C(x,y),G(x,y),X(x,y)) \quad (6)$$

When $T=T(G(x,y))$, it means the threshold is only related to the gray scale of the isolated image.

When $T=T(G(x,y),X(x,y))$, which means the threshold will be decided by the gray scale and other characteristics

When $T=T(C(x,y),G(x,y),X(x,y))$, implies that the threshold will be decided by the position, gray scale and other characteristics [22].

Because the input hand gestures are flexible and complicated, there is no universal method that can be applied to all gesture segmentation process. Much research has been conducted to find a proper threshold to get a good segmentation results.

Luigi Lamberti et al. [23] proposed using colour glove to recognise hand gestures. During the segmentation process, authors choose the least computationally complex segmentation method, the thresholding- based method. The basic concept is to classify pixels to different (seven) classes by using different thresholds. But the authors didn't reveal the details as to how they set up thresholds.

E. Stergiopoulou et al. [24] proposed a neural network shape fitting technique to recognise hand gestures. Authors used YCbCr colour space to segment the hand region. The thresholding selection is discussed in detail. They further drew up a map of the chrominance of skin colour by using a training set, while the training set includes several images about white hand poorly illuminated, white hand well illuminated and black hand well illuminated. They determined range of Cb and Cr values which is narrow and are very consistent with the existing data. It can minimize the noise and maximum skin colour detection rate.

3.1.1.4 Depth data

After capturing the image, the input image should be segmented, in order to obtain the gesture. The common methods of hand gesture segmentation are colour limitation or skin colour detection. The colour limitation method usually limits the environment by wearing coloured markers or using a fixed colour background. This approach leads to inflexibility of hand movements; however, it has much higher recognition accuracy. Skin colour detection method can directly separate the skin colour area from the input image, but it will be easily affected by the complex background and poor illumination. Besides, hand and face or other similar colour parts cannot be overlapped [25].

Availability of depth information of image objects can overcome these difficulties easily. The grey scale of the pixel in depth image is only related to the distance between the surface plane and camera, so the grey scale will not be affected by space colour, illumination and other colour factors. Besides, combined value of grey scale with horizontal and vertical coordinates, in a certain space, can be used to represent the 3D coordinates of an object. In other words, the depth data can be used for gesture recognition in 3D space [26].

In 1990s, the development of the time of flight (TOF) (Fig.4) camera resulted in measuring the depth information of an object by calculating the time of light flying [27]. Compared to the traditional 2D camera, TOF can easily determine background and foreground. It has unique advantages in target recognition and tracking. But TOF camera also features high price and low resolution [28].

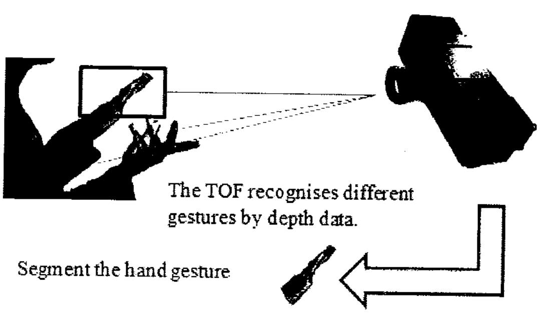

Fig.4 TOF camera system

In 2010, Microsoft developed the somatosensory peripheral 3D camera Kinect for Xbox 360 [29] [30]. It uses structured light coding techniques to obtain the depth information from the captured image. Kinect includes one RGB camera, one infrared camera and one infrared emitter. The emitter can send infrared laser, when the laser irradiates the coarse objects, it will form highly random diffraction spots, called laser speckle. The laser speckle will result in different patterns from different imaging distances. When the laser speckle irradiates the entire space, the whole image pixels are tagged. The infrared camera is used to transmit received tags to the internal graphic processor unit. This module produces the depth image with a resolution up to 640*480 and a low price. Besides, because of the additional graphic processor, it doesn't need too much computation ability of a computer. This has lead researchers to use Kinect for hand gesture recognition research.

K.K. Biswas proposed gesture recognition using Microsoft Kniect. [25] [20] The Kinect produces depth images of subjects (this is gray scale image). This gray scale image is used for isolating the hand region from the input image by using auto thresholding method. According to the depth histogram, the threshold is set to be the first fall down point which is the valley after reaching the first peak.

3.1.2 Feature extraction

The features are the useful information that leads to classification. Some features have properties of invariance. Rotation, scale or translation, illumination differences will not lead to misclassification. The features are extracted from the hand posture once it is isolated using image segmentation.

3.1.2.1 Features vectors

Good feature vector would be paramount for good classification. For this reason, much research is focused on forming effective features vectors. Features vector of the segmented image can be extracted in different ways according to particular application. Some methods used the shape of the hand such as hand contour and silhouette, while others used fingertips position, palm center, etc. A common method extracts the feature vector by dividing the segmented image into fixed block size and each block represents the brightness value in the image. Many experiments were applied to decide the proper block size that can achieve good recognition rate. In practical applications, it cannot be guaranteed that the image will not have translation, scale and rotation. These factors will highly affect the recognition accuracy [5].

Rajesh et al. [31] proposed a skin colour based method (L*a*b* Colour Space) to isolate the hand gesture from the input image; each hand gesture is centered to extract features. These features used to mark and count peaks and valleys of each gesture. Meanwhile the system divides the input image into sixteen parts to find positions of peaks and valleys. They combine number of Peaks and Valleys with its position of a gesture in the image to recognise the American Sign Language [33]. The recognition method is neural network. This method has one constraint, the hand should be well placed with proper ankle, but it doesn't require wearing colour gloves or sensor gloves. The test result shows this method can reach 100% recognition rate when applied to American Sign Language

Hamid A. Jalab et al. [32] proposed an algorithm to recognise static gestures using wavelets. Moreover, it implemented a feed-forward three-layer neural network with back propagation training algorithm during recognition process. Compared to the traditional Fourier methods, the wavelets-based algorithm has advantages in discontinuities of a signal. But this model is only applicable to static gestures. The experimental test result shows the classification accuracy of 97% (one hundred and twenty gestures have been trained and sixty gestures are used for testing).

A. Malima et al. [33] proposed a fast algorithm for robot control. Authors used a fast algorithm which can recognise a series of gestures applied for a robot control application. This system consists of hand region segmentation stage (skin detection method), locating the fingers stage (count the number of farthest distance between palm centre to finger point) and gestures classification stage. However, there are two prominent constraints in this system; when the system counts the number of fingers, it cannot differentiate different gestures with the same number of fingers, and moreover, this system can only be used for postures.

3.1.2.2 Hu moment invariants

The conception of moment invariants was proposed by Hu. Hu proposed 7 famous invariant moments which have been used in many image classification approaches. Seven invariant moments are extracted from an image which is not affected by translation, scale or rotation. Our research team has effectively used this approach for many classification problems in the past [38-40]. Equations 7-13 are the well-known Hu moments, which is a set of seven moment invariants are derived from the second order and third order moments.

$$\phi_1 = \eta_{20} + \eta_{02} \quad (7)$$

$$\phi_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}{}^2 \quad (8)$$

$$\phi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \quad (9)$$

$$\phi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \quad (10)$$

$$\varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})\begin{bmatrix} (\eta_{30} + \eta_{12})^2 - \\ 3(\eta_{21} + \eta_{03})^2 \end{bmatrix} + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})\begin{bmatrix} 3(\eta_{30} + \eta_{12})^2 \\ -(\eta_{21} + \eta_{03})^2 \end{bmatrix} \quad (11)$$

$$\varphi_6 = (\eta_{20} - \eta_{02})\begin{bmatrix} (\eta_{30} + \eta_{12})^2 - \\ (\eta_{21} + \eta_{03})^2 \end{bmatrix} + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \quad (12)$$

$$\varphi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})\begin{bmatrix} (\eta_{30} + \eta_{12})^2 \\ -3(\eta_{21} + \eta_{03})^2 \end{bmatrix} - (\eta_{30} - 3\eta_{12})(\eta_{21} + \eta_{03})\begin{bmatrix} 3(\eta_{30} + \eta_{12})^2 \\ -(\eta_{21} + \eta_{03})^2 \end{bmatrix} \quad (13)$$

η_{pq} is the normalized central moments, which can be calculated as:

$$\eta_{pq} = U_{pq} / U_{00}^{r} \quad (14)$$

$$r = [(p+q)/2] + 1 \quad (15)$$

$$p + q = 2,3,... \quad (16)$$

There are further improvements to the basic Hu moments as reported by [34]. The major difference in this approach is to use contour invariant moments.

Lihong Li et al. [34] proposed a system on pattern recognition, which has a high recognition rate by using discrete moment invariant algorithm. The basic idea of this algorithm is to combine the original moment invariants with contour moment invariants. The experimental result shows the recognition rate of the system can achieve over 98%.

3.1.3Gesture recognition

Recognition of hand gesture is the last stage of the hand gesture recognition system. After modeling and analysis of the input image, the system starts to recognize the gesture. Recognition process is affected by the feature extraction method and classification algorithm. Statistical tools are usually used for gesture classification. Neural network has been widely applied in the field of hand gesture extraction and recognition. Fig. 5 shows the basic recognition process. Before the recognition stage, the system should be trained with enough data so that a new feature vector can be classified with good accuracy [20].

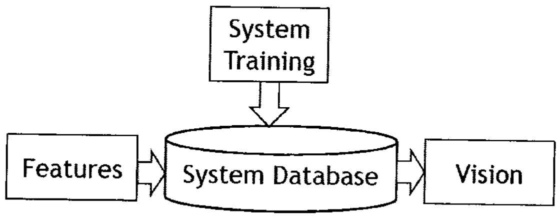

Fig.5 Gesture recognition process

HMM (Hidden Markov Model)

Up to now, many methods have been applied in hand gesture recognition area. As the dynamic hand gesture can be treated as the continuous motion on the time series, HMM can also be used in hand gesture recognition, and HMM is also one of the most popular approaches.

A HMM is a Markov Model (MM) with hidden parameters, which used the hidden parameters to ensure the state. The variants resulted from stats transitions are visible. But each state cannot be visible, each potential output has a possibility distribution. Hence the sequence of output includes the hidden information of the sequence of state.

In the context of hand gesture recognition area, a HMM can be shown as fig.5. X_1 to Xi represent the input states, which includes a set of hand positions in each state. The T_{ab}, T_{ba} represent the state transitions, which means the probability of transferring from one state to another state. The Y_1 to Y_i represent the corresponding outputs, which include one specific posture or one gesture [7]. So the database of HMM has many samples per single gesture, the relation between the number of samples and the accuracy is directly proportional, and between number of samples and the speed is inversely proportional.

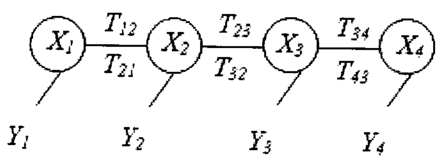

Fig.6 the Hidden Morkov Model (HMM) example

Byung-woo Min et al. [36] proposed a system of hand gesture recognition using HMM. They used 8 digit code to represent feature vectors. Each state is characterized by two sets of probabilities, a transition probability and either a discrete output probability distribution or a continuous output probability density functions. They set the number of states for recognition by counting the number of different states includes in one gesture. In their work, a 4- state HMM was used for hand gesture recognition.

Neural network

Especially self-growing and organized Neural Gas (SGONG), due to the characteristics of self-organization, self-learning and high anti-noise ability, the Neural Networks (NN) techniques have been widely applied in the field of hand gesture recognition [19](fig.7)

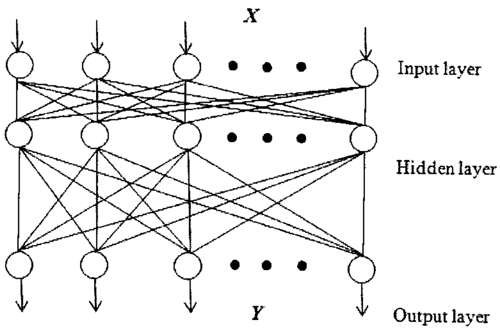

Fig.7 the structure of neural network

Nodes are the basic units in the neural network, the weight is the basic parameter between nodes (also called value vector). The above chart shows the simplest neural network. Assume the input are $X_1, X_2, \ldots, X_k$, the value vector between input layer and hidden layer is W_{ih}, the input from the input layer to the hidden layer is:

$$input = \sum_{1}^{h} W_{ih} X_1 \qquad (17)$$

The output from input layer to the hidden layer is:

$$W_i^m = f\left(\sum_{m-1}^{m} W_{ih} X_k + \theta_i^1\right), i = 1,2,\ldots \qquad (18)$$

Then the output of the hidden layer can be calculated as follows. [20]

$$Output = \sum_{1}^{k} W_{im} X_k \qquad (19)$$

If the output is not exactly the same with respect to results, the system will turn to operate reversely, it means the error signals will be returned along the original link to repeatedly change the coefficients of all layers until that the actual output is corresponded to the input.

E. Stergiopoulou et al. [28] proposed neural network shape fitting technique to recognize hand gestures. Authors use YCbCr colour space to segment the hand region. The SGONG network is applied to get the hand shape, then three features are obtained; Palm region, Palm center, and Hand slope. It will calculate the Center Of Gravity (COG) of the segmented hand and the distance from the COG to the farthest point in the fingers, and extracted one binary signal (1D) to estimate the number of fingers in the hand region. While the characteristics of palm are extracted, combine with the computation, the hand gesture can be identified.

Simei et al. [12] proposed a method of using boundary histograms and neural networks on static gestures. The feature extraction method results in a good recognition performance and lead to the significant reduction of processing time. They use boundary histograms to reduce the effects of rotation and deformable shape of the gestures. In their work, authors illustrated a new fast search start point algorithm for the boundary, which has a rotational invariance property. In the experiment, this model was tested using 26 postures of American Sign Language. The recognition rate has a complex relation with the number of histograms and histogram resolution. This method is only used for posture recognition.

4. Conclusion

In this paper, a comprehensive overview of hand gesture recognition system is presented to address problems and methods in each stage. In vision based hand gesture recognition approach, gesture recognition system comprises of four stages; gesture capture, isolation of region of importance (gesture) from the image, feature extraction and then gestures classification. Methods which are chosen in each stage highly affect the recognition performance.

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