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Vision-based Hand Posture Detection and Recognition for Sign Language-A study

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Abstract- Unlike general gestures, Sign Languages (SLs) are highly structured so that it provides an appealing test bed for understanding more general principles for hand shape, location and motion trajectory. Hand posture shape in other words static gestures detection and recognition is crucial in SLs and plays an important role within the duration of the motion trajectory. Vision-based hand shape recognition can be accomplished using three approaches 3D hand modelling, appearance-based methods and hand shape analysis. In this survey paper, we show that extracting features from hand shape is so essential during recognition stage for applications such as SL translators.

Keywords: *hand detection, hand posture recognition, feature extraction.*

1. INTRODUCTION

Hand shape recognition is a widely studied topic which has a wide range of applications such as Human Computer Interaction (HCI), SL translators, gesture recognition, augmented reality, surveillance and medical image processing etc. Hand posture recognition with no constraint on the shape is an open issue because the human hand is a complex articulated object consisting of many connected parts and joints. Considering the global hand pose and each finger joint, human hand motion has roughly 27 degree of freedom (DOF) [1]. Hand detection or hand segmentation is usually used as a preprocessing step for higher level vision tasks. Many approaches have been developed based on skin color, movement of the hand, fingertips and the pattern detection methods [2, 3, 4, 5, 6, 7, 8, 9].The approach to vision-based hand posture recognition can be divided into three categories; 3D hand model based approaches [10], appearance based approaches [11] and hand shape analysis [12]. Most of the researchers' effort on hand shape recognition has focused on hand modelling and appearance-based approaches, which attempted to establish a mapping between the image feature space and the hand configuration space [13,14,15]. For applications such as SL, gestures are treated as a sequence of hand postures connected by continuous motions. Though a decomposition of hand postures could be recognized individually to form a word but hand modelling and appearance-based approaches could work as ad-hoc in this stage. Hand shape analysis can be useful whenever it is difficult to analyse hand feature directly from images with low resolution. This paper surveys studies on vision-based static hand shape detection and recognition techniques. The organization of this paper is as follows; Section 2 surveys methods used for hand detection or segmentation. Approaches used for static hand posture recognition are reviewed in Section 3. Section 4 states the conclusion.

2. STATIC HAND POSTURE DETECTION

The first step in SLs systems is to detect and track both hands, however this is a complex task because hands may occlude each other's and/or face. Furthermore, extracting the palm area from other skin areas is another important issue. Some researchers used markers on hand and fingers [12] to achieve the task. Others used barred hands and developed different approaches as stated below.

2.1 Approaches with Assumption: Hand only is in the Field Of View (FOV)

Various assumptions are used during hand segmentation stage, such as the hand being the only skin-colored object in the scene, uniform ambient lighting or stationary background.

A. Skin Colour Approaches

Systems that employ skin-color based hand detection [2, 3, 16] are not reliable by themselves. Hands have to be distinguished from other skin color objects and there are cases of insufficient lighting conditions [5, 17, 19]. Bretzner et al. [8] use a hand detector by including skin colour information in the form of a probabilistic prior. Meanwhile hand is the only object in the plan, [18] propose to use the uniform *YCbCr* color space in order to dissociate the luminance from the color information to extract hand for gesture recognition. However, it is not reliable to model a skin color for people of high variations of skin colors and under different lighting conditions. Limitations arise from the

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fact that human skin has common properties and that it can be defined in various color spaces after applying color normalization. So the model has to accept a wide range of colors, making it more susceptible to noise.

B. Approaches with Static Background Inclusion

Assuming that the hand is the only object in the FOV, back ground subtraction methods gives good results. Often the background is assumed to be static, and known [19, 20].

2.2 Approaches with Assumption: the Whole Human Body is in FOV

In SL systems, it is not practical to assume that hands are the only object in the scene. Non manual signs such as facial features are so crucial as well to be recognized. Hence, the upper human body must appear in FOV.

A. Approaches with Motion Constraints

Hand segmentation based on skin color has many limitations as stated in Section 2.1. Therefore, motion flow information is another modality that can fill this gap under certain conditions [4, 7, 19, 21, 22, 23, 24]. These systems assume that the hand is the fastest moving objects in the image frame.

B. Appearance-Based Approaches

On the other hand, there are few systems that operate in an appearance-based detection framework. In [29-31] Haar like features are used for the task of hand detection. Kolsch and Turk [5], Ong et al [6] developed a system for detecting hands based on AdaBoost but their approach is view-specific, i.e. limited to a few postures of the hand.

3. STATIC HAND POSTURE RECOGNITION

There are many approaches that have been proposed for hand segmentation and extraction from the background. Furthermore, hand posture recognition is an advanced step from hand detection. Since it is not an easy task to differentiate between signs with the same trajectories but different posture shape see Fig. 1, hand shape plays an important role in such satiations.

It involves that the hand shape should be translated to an understandable form in applications such as SL.

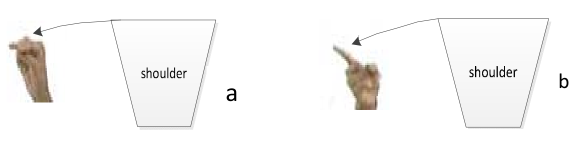

Figure 1: Malaysian SL (MSL) stands for (a) We (b) She

3.1 3D Hand Model Based Approach

There are many methods already developed to deal with hand modelling and analysis which offer a rich description that potentially allows a wide class of hand shapes. However, as the 3D hand models are articulated deformable objects with many DOFs see Fig. 2, a very large image database is required to cover all the characteristic shapes under different views. Another common problem with model based approaches is the problem of feature extraction and lack of capability [25] to deal with singularities that arise from ambiguous views. [26, 27] provide a complete review of 3D hand modeling approaches.

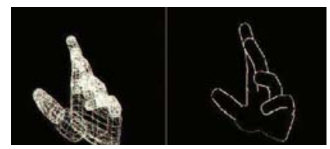

Figure 2. The 3 D model (left) and its generated contour (right)

3.2 Appearance-Based Approach

Appearance based approaches use image features to model the visual appearance of the hand and compare these parameters with the extracted image features from the video input. These approaches have the advantage of real time performance due to the easier 2 D image features that are employed. There are many approaches uses appearance based approaches for hand shape recognition as well as hand tracking and can be summarized as follows:

3.2.1 Local Invariant Features

Real-time applications require fast computational time and this is applicable when local invariant features approaches [28, 29, 30, 31] is used. In [18], AdaBoost learning algorithm is used with scale invariant feature transform a histogram representing gradient orientation and magnitude information within a small image patch. However, different features such as contrast context histogram need to be studied and applied to accomplish hand posture recognition in real time. Some approaches [25-29] use Haar-like features which focus more on the information within a certain area of the image rather than each single pixel. AdaBoost learning algorithm that can adaptively select the best features in each step and combine them into a strong classifier was used.

3.2.2 Eigen values

View-based object representations have found a number of expressions in the computer vision literature, in particular in the work on eigenspace representations [32, 33].The eigenspace approach seeks an orthogonal basis that spans a low-ordered subspace that accounts for most of the variance in a set of example images. To reconstruct an image in the training set a linear combination of the basis vectors (images) are taken, where the coefficients of the basis vectors are the result of projecting the image to be reconstructed on to the respective basis vectors. In [13] the authors present an approach for tracking hands by an eigen space approach.

A. Principal Component Analysis (PCA)

Some are based on deformable 2D templates of the human hands, arms, or even body [34], [35], [36], [37], [38]. Deformable 2D templates are the sets of points on the outline of an object, used as interpolation nodes for the object outline approximation. The simplest interpolation function used is a piecewise linear function. The templates consist of the average point sets, point variability parameters, and so-called external deformations. Average point sets describe the "average" shape within a certain group of shapes. Point variability parameters describe the allowed shape deformation (variation) within that same group of shapes. These two types of parameters are usually denoted as internal. For instance, the human hand in open position has one shape on the average, and all other instances of any open posture of the human hand can be formed by slightly varying the average shape. Internal parameters are obtained through PCA of many of the training sets of data.

3.2.3 Approaches Use the Whole Images

Since the appearance based approaches and 3- D modelling methods have some limitations, other researches use the whole image as input and features are selected implicitly and automatically by the recognizer.

Bretzner et al. [8] demonstrate how a real-time system for hand tracking and hand posture recognition can be constructed combining shape and colour cues.

Cui and Weng [39] classify hand signs by partitioning the Most Discriminating Features (MDF) space. A manifold interpolation scheme is introduced to generalize to other variations from a limited number of learned samples. Triesch and Malsburg [40] employ the elastic graph matching technique to classify hand postures. Since using one graph for one hand posture is insufficient, this approach is not view-independent. Quek and Zhao [41] introduced an inductive learning system which is able to derive rules of Disjunctive Normal Form(DNF) formulate. Each DNF describes a hand pose, and each conjunct within the DNF constitutes a single rule. Nolker and Ritter [42] detected the 2D location of fingertips by the Local Linear Mapping (LLN) neural network mapped them to 3D position by the Parametric Self-Organizing Map (PSOM) neural network which can recognize hand pose under different views.

3.3 Hand Shape Analysis

Selecting good features is crucial to recognize hand shape, since hand gestures are very rich in shape variation and textures. We have addressed that the 3D modeling methods is however computationally rich in recognition and appearance-based approaches are view-specific, i.e. limited to a few postures of the hand. After the segmentation of hand is achieved, there are two types of features can be extracted either statistical features or geometrical ones from the coloured image or binary image.

3.3.1 High Level Features

High level features such as fingertips, fingers, joint locations, and the links between joints are very meaningful [2, 43] but also very difficult to obtain from the segmented hand shape. The algorithms that require direct extraction of fingers information fall under two categories:

A. Approaches Using Markers

Employing markers could be inconvenient but extraction of high level features often rely on them to extract fingertips, joint locations or some anchor points on the palm [44, 45, 46]. Kin et al [47] used white fingertip markers under black light for gesture recognition. Assuming a clutter-free background, it is possible to extract some high level features without any markers.

B. Markerless Approaches

Fingertip detection can be handled by correlation techniques using a circular mask [48, 49, 50], which provides rotation invariance, or fingertip templates extracted from real images [51, 52]. Using curvature local maxima on the boundary of the silhouette is another common method to detect the fingertips and the palm-finger intersections [53, 54, 55]. Sensitivity to noise can be an issue for curvature-based methods in case of noisy silhouette contours. A more reliable algorithm based on the distance of the contour points to the hand position is utilized in [56, 57]. Some researcher uses a fingertip extraction algorithm based on Gabor filters and special neural network architecture (LLM-net) [58]. Contour analysis was performed by [59] to detect the intersections of the fingers and the palm. Ravikiran et al. [60] detected the fingers using the boundary tracing combined with finger tip detection. However the method cannot detect which fingers in particular are open. Furthermore, finger or 2D hand orientation can be estimated by calculating the direction of the principal axes of the silhouettes [61, 62, 63].

3.3.2 low Level Feature

Contours or edges are somewhat universal features that can be used in any model-based technique [64] as well as non-model ones. The aim is to have similar values of features for similar hand shapes and distant values for different shapes. It is also required to have scale invariant features so that images with the same hand shape but different size would have the same feature values [12].

A. Fourier Descriptors (FD)

FD are calculated on the contour of the hand region and points of this contour can be represented with various signatures (complex coordinates, central distance, curvature, cumulative angular function) [65]. [66] applied the FD for hand recognition but before calculating the Fourier Transform, the contour is sampled to obtain a normalized contour length with the Fast Fourier Transform (FFT). The sampling is done by interpolating points which are at an equal arc length to obtain good shape descriptor.

B. Statistical Features

Moments are used to describe the properties of objects shape statistically.Hu [67] derived a set of seven moments and it has been extended by Maitra [68] to be invariant under image contrast. Later, Flusser and Suk [69] derived the moment invariant under general affine transformation. The hand shape was recognized in [70] by using Hu-Moments set which are translated, orientated and scaled invariant as a statistical feature vector and the recognition has been achieved using SVM .

C. Geometrical Features

These features are computed to exploit the hand shape with the standard shapes like circle and rectangle [70]. They vary from symbol to symbol and are useful to recognize hand postures.

4. CONCLUSION

In this paper, we have presented an extensive survey of various techniques for static hand detection and recognition. Most of the systems for gesture recognition have used only motion trajectories but SLs translators' structure involves both static and dynamic gestures to differentiate between signs. When a signer starts signing, hand shape plays a crucial role because gestures with the same motion trajectories could not be recognized in the absence of hand shape. Many methods have been developed for hand shape recognition but real-time applications require fast computational time as well as the storage requirements which are extremely important. The features have to be scale invariant and not limited to certain hand shapes which give flexibility to the SL recognition systems.

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