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Research trends in Hand Gesture Recognition techniques

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Abstract: ***Over years' key board and mouse are among the most effective input devices to the computers. Not much improvement has happened for other modes of inputs like voice and gestures. These kinds of inputs explore the limitations caused by the key board and mouse, which needs actual physical contact. With gestures and voice the physical proximity can be little relaxed and can be used by specially-abled people. Exploring effective Human Computer Interactions (HCI) has always been of great interest for development of new techniques and methods. Gestures are considered as more easy, natural, and intuitive method for communicating with systems. Hand recognition and analysis forms the core of these systems. This paper provides comparative study on state of art technologies that work in this area. The different representation, detection and recognition techniques are discussed. The strength and challenges of different techniques are highlighted. The main aim of this research is to summarize the research progress done till date with different technologies for gesture recognition algorithms, identify areas which need further research.***

Keywords: Hidden markov model, Neural networks, Probabilistic Models.

I. INTRODUCTION

Powerful and more visible human to human communication in everyday life happens through Hands. When a person is communicating with another, one of the very natural and powerful ways of interactions is to make gestures using hand. One of the very powerful forms of nonverbal communication is through hand movements. It is one of the effective visible media for information transfer between the two persons. Meaningful understanding and classifying gestures made by human hand is the purpose of hand gesture recognition system. Actually hand is very small, compared with the entire human body, yet very complex articulations are made. Hence accurate analysis is required, and must have very low error tolerance. Hence it is a very challenging research area to work on. It is of great significance and relevance in designing artificially intelligent Human Computer Interaction (HCI). This paper is about the existing methods in detecting, tracking and recognizing hand gesture techniques. It briefly compares performances, accuracy, efficiency, and design challenges of these techniques. Most of the hand gesture recognition systems are about image acquisition, pre-processing and gesture recognition. Image acquisition is about fetching the images that must be analyzed for gesture recognition by any image acquisition hardware like a camera module [1]. The acquisition modules will vary for different systems. It can be sensors or data gloves or a camera module. Pre-processing needs to be done on the captured images. It is the step where the information in the image is enhanced after acquisition. This ultimately improves the accuracy of the recognition system. The different pre-processing operations are filtering, thresholding, histogram equalization, edge detection [1,2]. Recognition identifies or classifies the processed hand movement as particular gesture. In real-time system it is required to recognize the gesture immediately when it is made and appropriate action need to be taken. Faster analysis, accuracy and robustness are the important criteria's for comparing different recognition systems. Intensity variations, cluttered and varying backgrounds and occlusions are the main challenges to deal with in the recognition systems. The position and orientation of hand for a certain time without causing any motion is termed as Static hand gestures. And if there is a movement during that period it is called Dynamic hand gesture. A gesture like waving of hand is Dynamic gesture. Gestures like circle ling the thumb finger and fore-finger to form the "OK" symbol is called Static gesture. 3D model based and vision or appearance-based methods are two main categories in hand gesture recognition system. The 3D based approach uses techniques like texture volumetric model, geometric model and skeleton model. Vision based hand gesture representation uses techniques like silhouette geometry, color-based, texture-based, deformable edge based and motion-based models.

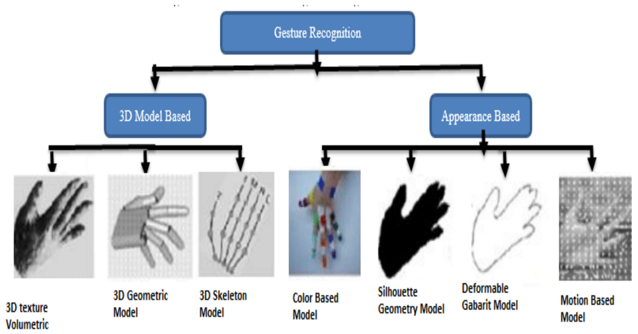

Figure 1: Vision based hand gesture representation

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Vision or appearance-based gesture representation uses either 2D static model or motion-based model. These systems mainly consist of segmentation for detection, tracking and classification or recognition. Firstly, the hand segmentation in the image frame region will be done.

By doing this object data and its back ground information will be separated, and then the segmented data is detected as hand and then passed to the subsequent modules. There are many methods proposed that uses several types of vision-based features and their combinations like skin color [3], depth data [4], motion, shape and anatomical models of hands [5].

The detection module must process at image acquisition module rate. That means detection should happen very quickly and must make way for tracking and recognition modules. However, tracking hand is very tedious procedure as hand can move very quickly and its visible features can change drastically within a few frames. Segmented hand regions are defined and its frame by frame information analysis [6] is called Tracking. Information will be the features corresponding to the hand movements [7]. The extensive tracking has many advantages. It provides the linking of features across frames, thus giving the mapping of features in temporal domain. These feature map give the required information about the hand gesture tracking and will be used for further analysis for recognizing the gesture.

Semantic analysis of gesture means to understand what it conveys. This will be the primary purpose of all the hand gesture recognition systems. Among gesture analysis there are two main approaches. They are static and dynamic. For static, template matcher is used for classification. But for dynamic gesture analysis in time domain is required. Hidden Markov Model (HMM) handles the modelling of temporal dimension. It implemented as a state transition path from an initial state to a final state. Automata representation of hand gestures. The main limitation of this approach whenever a new gesture needs to be recognized, the whole model has to be redeveloped. Hence the main challenge is the high computational complexity. It is directly depending on the number of gestures to be identified.

For any object detection, many methods use motion or color information [3, 4]. In [6] shape analysis is used for static gesture recognition. In [7] they have proposed a method by which color segmentation is used of the hand region detection. In [4] depth data is used for hand gesture recognition. [10] have proposed a very interesting method that uses R-MINI Algorithms and AQ Family Algorithms for the detection of gestures. Hidden Markov models have been suggested for hand gesture recognition in [9]. [8] suggested the Input-output Hidden Markov Models for gesture recognition. [12] proposed HMM based on thresholding. In [13], they presented a method called PCA-HOG global descriptor for recognizing human gestures. [11] presented another efficient technique that uses Fast Multi-Scale Analysis for recognizing hand gestures, but this method is computationally costly. Rotation Invariant features like texture is popularly used for classification and recognition. [14] have proposed similar method for enabling dynamic hand gesture recognition. [15] have proposed Local Binary Patterns method for texture classification.

In [16] and [17] extensive research surveys have discussed some of the cutting edge technology for vision-based hand gesture recognition techniques that are under research. Some of the key techniques are discussed in subsequent units.

II. TEMPLATE MATCHING

The detected hand has to be tracked in consecutive frames. Tracking can be achieved by template matching between consecutive frames. There are two ways of template matching, correlation based or contour based. If the detected or segmented region is used as a prototype for detection in further frames, then it is correlation based matching. In this method, variations in intensities and motion of the object are taken care. By pre computing the template to be matched computational time cane be reduced. The object template is calculated by considering the spatial derivatives in the reference object and a set of supported motion vectors. Sometimes the hands are detected as image blobs and their occurrences in close by locations in consecutive frames are tracked. This type of tracking can be used when skin colors are used for object segmentation. This is one of the efficient methods of tracking.

In contour-based template matching, tracking in successive frames are done by deformable contours. Contour is framed around the area of object. It will be then repeatedly and smoothly reformed at the corners and edges to properly fit the object. It gives better results when the contrast between the object and its back ground is high.

A. Filtering

Filtering provides optimal framework in object tracking. Kalman filters are widely used for the tracking the detected feature by estimating its trajectory. It is very effective for successive predictions, real time performance and working with uncertainty [18]. It gives an optimal framework for turning observations in to estimations. It handles occlusion effectively based on hypothesis formation and validation/rejection approach [19]. In [21], using multiple cameras hands are tracked, using Kalman filter, 3D hand posture in estimated. In Kalman filtering framework, Snakes can integrate for tracking [22].

In visually cluttered dense video, Particle filters are used to track position of hand and configuration of fingers [20]. In Particle filter approach, the set of particles will model the hand and the location is also tracked. This Particle filters shows advantage over Kalman filters as it is not limited by Gaussian densities. Kalman filters use unimodal Gaussian densities that cannot represent another hypothesis. But the drawback of Particle filters is that it is complex for high dimensional models, too many particles will be required. This can make it intractable.

In [23], Condensation algorithm is used to track curves with cluttered background. The author shows that the performance is better that Kalman filters and works more efficiently in real time. Factored samples are first applied to static image interpretation.

Randomly generated set with probability distribution is used for tracking. Dynamic models with visual observation and random set are part of Condensation. As a result, very highly robust tracking of agile motion is achieved.

In [24], the motion is detected through basic transformation like 2D translation, scaling and planar rotation. In [25], condensation algorithm is extended to detect occlusions. In [26], condensation algorithm is integrated with color information. This is the principle for color histogram with probabilistic framework. Monte-Carlo tracking technique will be used.

B. HMM

In mid 1990s, the segmentation problem found a solution by one recognition method called Hidden Markov Model.

In [27], HMM is described using Markov chains. Markov chains are designed as finite state automata with probability values associated with every state transition. The probability values of transitions leaving a state will always add up to one. It also restricts that the finite state automaton makes one transition for a given input. Hence it is deterministic finite automata. HMM considers generalized Markov chains without this restriction. So HMMs can have more than one transitions for a given output. They are non-deterministic. That is, it is not possible to determine the sequence of states for a given set of outputs. Hence the term hidden in HMM. Basically, HMM is a sequence of states with one initial state, set of transitions, set of output symbols and a probability values associated with each transition from one state to another. In case of hand gesture recognition, every state represents some hand positions. The probability represents the deviation supported for a particular gesture. The output represents a specific posture. Sequence of outputs represent the hand gesture. Hence one HMM model represents one gesture. So many applications can use set of HMMs.

In [12], HMM is used for two hand gestures using trajectory features. It uses forward algorithm for selecting the key frame and pixel to pixel distance measure. Novel HMM methods are used for key frame selection. The main advantage of this method are the pixel and shape distance calculations are done for key frames only. Hence the calculation for all frames in video sequence, are not required. This improves the speed efficiency. Thus key frame based gesture recognition for very useful for quick recognition and for working with videos in compressed domain.

In [28], forward algorithm of HMM uses test frame T and standard frame S. It compares the two frames to find the probability of the given sequence. It compares State transition matrix with confusion matrix using forward algorithm [29] [30]. If the result of comparison satisfies the given requirement, then it is successful gesture recognition otherwise non gesture phase. Next step for both single and double hand gesture recognition is to identify the features. It is very important to identify the correct features. It is directly related to the performance of recognition system. Usually the shape, color and motion are used features. We need to consider both static and dynamic features for trajectory matching. To identify the global motion, dynamic features will be used. Usually for hand trajectory static feature correspond to shape and dynamic feature correspond to motion [31]. Generally static features map to low level features and dynamic features map to higher level features. And both play an important role in identifying the gestures. The six features used for recognition are key trajectory point, trajectory length, orientation feature, location feature, acceleration and velocity.

C. Adaptive Probabilistic Model

Particle filter is integrated by a deterministic cluster. This framework is used in real time. To segment the human hand skin color feature is used. By adaptively using Bayesian classifier human hand is segmented from the captured image. Next a matching algorithm is used to determine the probability of the finger tips using fingertip mapping. Then the ROIs are created by developing standard particle filter using the clustering algorithms. These ROIs are used for tracking. After hand region segmentation, identifying the fingertips are done [32]. Finally, the fingertips and location of human hand are visibly tracked. The luminance changes are effectively handled. Semicircle models are used for fitting curves in fingertips. Then it is used for calculating probabilities of occurrence. To deal with different orientations, sizes and colors of the fingers, different models are developed. Summing the results of Fingertip model matching, gives more efficient results than other combinations like using maximum of matches. Weights are assigned to all models and weighted sum is considered so that all models contribute to the result. ROIs are identified by searching using deterministic clustering algorithm. For tracking the segmented fingertips successfully, Sequential Monte Carlo algorithm can be used. In [33], the Monte Carlo algorithm's advantages are highlighted. Automatic initialization of Track and recovering from the failed track are shown successfully. Hence even when the fingertips disappear and reappear, the system can still track them successfully due to the advantage of particle filter.

D. Artificial Neural Networks

Artificial neural network focus on analysing real time continuous data. These architectures are adaptable for online networks. This makes it very effective for real time systems. Actually, time delay networks are derived from multi-layer perceptron. In [34], each neuron gets the capability to store information of their input history based on time delays. Hence it is possible for the network to work on any pattern sequence. Because of time delays each neuron will have the inputs present at time t1, t2 … tn. Along with the past it has access to input information at current time t. Hence it can detect and analyze the input sequence, the dependence between current and previous inputs. The network can also approximate and predict the sequence that are called from the input using history of information available. Standard back propagation algorithm and its variations are popularly used algorithm for learning in TDNN systems. Neurons are the center of information processing in these network models. Neurons pass signals over a connection links.

Weights are associated with each connection link. These weights are derived by typical neural net and signal transmitted. Every neuron has a nonlinear activation function for its sum of weighted inputs. In multilayer neural network, there will be a hidden layer between the input and output layer.

This is the layer of weights. This can solve more complicated problems but training these models are equally challenging. The system can be developed only by learning. Programming is not possible. It is ideal for changing environment.

In [35], the system is modelled to identify hand gesture in real-time. The algorithms used are normalizing, equalizing the histogram and greying. On getting a grayscale image, noise is removed from the input image using Median filters. Binarization is achieved by using adaptive local thresholding algorithm. Features for hand gesture are extracted. The features like basic transformation like translation, rotation and scaling are developed. Other orientation independent feature extraction methods are used. Feed forward multilayer ANNs are used in [36]. In figure 2, the network architecture is 33-85-4. There are 85 hidden neurons. They are calculated by the input vector with 33x20 dimension. The output layer has 4 neurons mapping to four outputs. This network is called fully connected and learns using back propagation algorithm [37]. Figure 3 is the architecture of the network is 33-85-4. Here 85 hidden neurons are used, 33 × 20 intermediate layer and 4 output neurons as there are 4 outputs of the network. This network is fully connected and uses back-propagation learning algorithm [37].

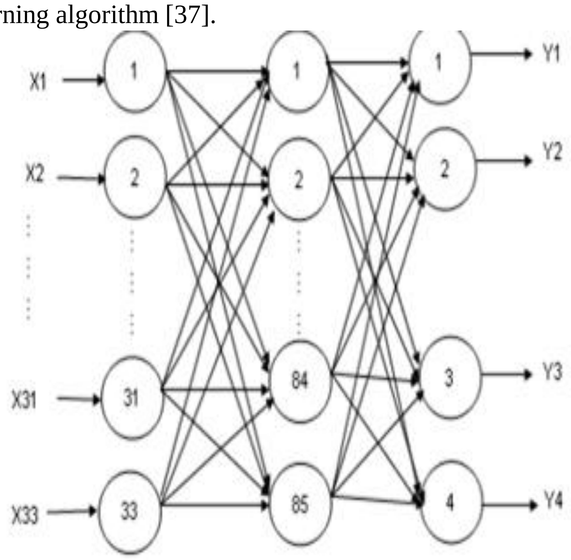

Figure 2: ANN design for the system

E. Convolution Neural Networks

In fully connected networks, each neuron in one layer is connected to all neurons in the next layer. This refers to Multilayer perceptron and a more regularized versions are called CNNs. The fully connected nature of these networks causes the data to be oversized. Regularization is varying the magnitude of the weights to the loss function. In CNN, regularization takes a different procedure by taking hierarchical pattern in data. It assembles the smaller and simpler patterns and makes complex patterns. Connectedness and complexity are given high priority. CNNs are inspired by biological models like animal visual cortex resembles connectivity pattern among neurons. Compared to other classification algorithms for image, CNNs use very minimum pre-processing. That means hand written algorithms are replaced by network learning filters. And this becomes the major advantage of CNNs. Independence from prior knowledge and human effort in designing the algorithm. In [38], 3D CNNs uses intensity and depth in channels for hand gesture recognition.

And in [39], the two channels are interleaved to build spatial and temporal normalized volumes. It trains two separate subnetworks. An effective spatial and time related data augmentation technique is used to improve the classifier and reduce the data overfitting problem. As shown in figure 3, the input to the classifier are 57x125x32 volume of image data. It mainly consists of depth and gradient information. Further the classifier generates two sub networks: (HRN) High Resolution Network and (LRN) Low Resolution Network. These subnetworks generate class membership probabilities. Finally, these two networks are merged by multiplying their respective class probabilities.

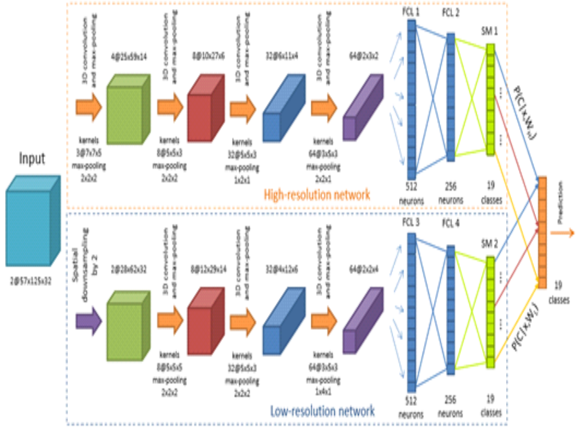

Figure 3: CNN design of the system

In [40], CNN extracts features and artificial neural network (ANN) is used for classification. Max-pooling is used, where maximum among local neighbourhood among feature maps are used. It is performed in all the dimensions to processes the video data. The architecture has modelling two CNNs, one for hand feature extraction and one for body feature extraction. There are three layers in each CNN. There is one hidden layer in conventional ANN classifier. It is concatenated with the results of both CNNs. In [26], the first two layers uses Local Contrast Normalization (LCN) and in [27], all neurons are Rectified Linear Units (ReLU). This architecture is shown in Figure 4.

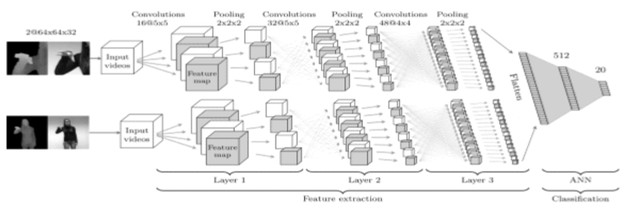

Figure 4: The architecture of Deep Learning Model

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III. RESULT AND COMPARISON

Table 1 shows the comparative analysis between various techniques used for hand gesture recognition:

Technique	Principle	Advantages	Limitations
Template Matching	The image regions are treated as prototypes for detecting the hand in the subsequent frames.	Implementation is straight forward. Better performance when contrast variation	Templates for tracking are precomputed to fasten the processing for real-time systems. Challenging when background is cluttered.
Filtering	Kalman-filtering, Particle filtering, Condensation algorithm are used. Set of particles are modelled as hand.	Possible to predict successive frames, real time performance achieved, uncertain situation handled	Challenging for high-dimensional models
Hidden Markov Model	Markov chain is used.	Efficient, faster and can handle both static and dynamic gesture recognition	Large training data, some assumptions made about the data, number of parameters are high
Adaptive Probabilistic Model	Skin coloured region segmented by Bayesian classifier. Matching and clustering algorithm for tracking fingertips	Better results for embedded system application with limited power and processing time	Accuracy need to be improved for finger self-occlusion caused due to multi cameras
Artificial Neural Network	For recognition, back propagation algorithm and feed forward neural networks are used	Complex back ground and illumination variations affect the performance	More suitable to work in hybrid systems. HMM with ANN or CNN with ANN
Convolution Neural Network	Depth and image gradient used, normalized fused motion volume considered, spatio-temporal data augmentation done, low- and high-resolution sub networks used.	Data over fitting avoided; a sub network improves c lassification accuracy considerably. Better performance achieved.	Need to improve on classifiers that work on higher level dynamic features

Table 1: Comparison between various techniques for hand gesture recognition

IV. CONCLUSION

For many years it has been a challenge to effectively interact with the computing device using hand gestures. It is one of the leading areas of research. In this paper, many latest technologies are considered and compared by referring the latest publications in major journals and conferences. It gives brief overview of core technologies related to hand recognition. The advantages and the challenges of the techniques are highlighted. The challenges faced by many of the techniques are occlusions, illumination changes, poor resolution, high frame rate.

Vision based gesture recognition techniques are less complex and implementation easy than the 3D model-based gesture recognition systems. Complexity and efficiency are always giving challenges for the technologies to handle. Any advances in man to machine or machine to machine will always scales up the industrial demands.

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