Gesture based imitation learning for Human Robot Interaction

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***Abstract*—This paper describes a gesture based recognition system using Indian Sign Language (ISL) for performing Human Robot Interaction (HRI) in real time. It permits us to construct a convenient gesture based communication with humanoid robot HOAP-2. The classification process is carried out by extracting the features from ISL gestures. Orientation Histogram is considered as a feature vector for classification process. It is to be done by the two statistical approaches namely known as Hidden Markov Model (HMM) technique and Bhattacharyya Distance estimation in order to achieve satisfactory recognition accuracy. The major task involves by computing the recognition time taken by both the above methods and finally the suitable one participates for HRI applications. The classification result has been tested on the Webots simulation platform on Humanoid robot (HOAP2) to generate mimicry according to the recognized gestures.**

Keywords—Human Robot Interaction; Indian Sign Language; Vector Quantization and LBG algorithm; Hidden Markov Model; Bhattacharyya Distance; WEBOTS simulation software for HOAP-2 humanoid robot

I. INTRODUCTION

Gesture based recognition is one of the most promising areas in research appealing its huge applications [28]. An intelligent framework is being built with gesture in order to accelerate Human Robot Interaction accurately. We have chosen suitable recognition techniques for the establishment of gesture based communication with humanoid robot HOAP-2. According to the different researcher point of view, HMM is a very well acceptable method for gesture recognition. But, we find that it takes more time to recognize the gesture. For this reason we are trying to find a different method which gives same accuracy to recognize gestures but within a very short period of time.

Indian Sign Language has its own grammatical and syntactical meaning in the linguistic form of signs. It implies a visual-spatial language which consists of hands, arms, and facial expression and head or body postures in such a manner that linguistic information could be provided significantly. The construction of ISL gesture [1, 28] can be defined by several parameters like shape of the hand, location of the hand movements in a straight or circular way, orientation of the hand, facial expressions, body or head posture and eye gaze. The gestures primitives are being captured by Indian Sign Language symbols. It imparts a challenge in terms of its complex symbolic gestural representation and proper linguistic understanding. It would be used as a helping agent for interpreting the knowledge among hearing impaired people in their own community. It will increase their strength of conversation in an extreme extent. This paper tries to introduce the strategy for dealing with the dynamic hand gesture recognition with reduction of time which will really be helpful for designing a concrete HRI system. It incorporates the challenges to extract the dynamic feature from the continuous signals.

The current prototype strongly supports the mimicry on humanoid robot HOAP-2 in real time. The further expansion on recognition includes the translation system between verbal expression and sign language. This system would be useful for hearing impaired people for exchanging information among them through the HRI approach. This demands a real time gesture recognition system by translating sign language. The unique and novel techniques using Bhattacharyya Distance and HMM have been applied separately in our current system to recognize the ISL gestures and generate mimicry by the humanoid robot accordingly. Then we try to identify a suitable recognition system according to the time taken for recognizing the gesture.

The entire paper has been constructed in the following manner: Section II describes the related works already done in this area. Section III describes the mechanism of ISL gesture acquisition. The Next section explores the gesture preprocessing technique with proper feature selection followed by evaluation technique. Section V expresses the recognition techniques with Hidden Markov Model based approach and Bhattacharyya distance estimation among all the samples of ISL gestures. The Next section demonstrates the mimicry by the humanoid robot HOAP-2. Section VII presents the experimental results. The conclusion including future work has been attached in section VIII. References are included at the end of this paper.

II. RELATED WORK

Numerous amount of work on recognition of static sign language symbols has already been done. The KHU-1 data glove [2] based approach has been used for 3D hand motion and tracking and recognition of hand gestures. The recognition of Chinese Sign Language [3] using a data glove based system has been done using only static symbols. In this paper we have figured out the recognition process with the data glove based approach considering as an input device for extracting features from hands. Ishikawa M, Matsumura H, have proposed a recognition system based on a self organization method [4]. The entire recognition process has been followed by acute measurement of finger joints using a data glove, extracting the gestures out from a sequence of hand shapes and proper aligning of data length. The most elegant process for recognition of Malay Sign Language using wireless data gloves is described [5]. A data glove is used for recognition of continuous gesture considering huge number of vocabulary in Taiwanese Sign Language (TWL) [6]. The key glove concept [7] presents a new input device for human hand motion recognition. A novel approach is being used for classification of Croatian sign language [8] using K Nearest Neighbor method with Dynamic Time Wrapping (DTW) and Longest Common Subsequence (LCSS) for similarity measurement. In our approach dynamic hand gesture recognition has been done considering both hands simultaneously. It is the composition of spatio-temporal signal which could be analyzed in an elegant manner. The synthesis of motion data extracts salient features from hand motion signal for recognition purposes.

A single video camera based recognition system deals with the recognition of German Sign Language [9] with considering hand arm motion. Unlike the data glove based, vision based gesture recognition for human robot interaction [10] has been entertained effectively. Another approach deals with the recognition of Chinese Sign Language [11] towards implementation of human robot interaction. A probabilistic framework [12] is applied for recognition and reconstruction of gesture for humanoid robot which is composed by PCA, ICA and HMM techniques. Kinesthetic demonstration by a human operator enables the humanoid robot to learn the gestures. Humanoid robot can be trained by applying imitation learning techniques [13].The portrait drawing [14] is a challenging task performed by humanoid robot HOAP-2.

III. ISL GESTURE ACQUISITION SYSTEM

The prime focus on recording ISL gesture is to create a repository with dynamic ISL video (sequence of images) gestures from different kinds of ISL class/word dictionary. Preliminarily, ISL dynamic gestures have been recorded with fixed frame rate per second (15 fps) and with the fixed location of the camera from the object. The samples of ISL gestures are to be used during the classification process. All the ISL gestures include various kinds of hand motions. A capturing device SONY handy cam with 2.5 mega pixel resolutions is used for capturing videos of several ISL gestures. In recognition purposes, limited specific dynamic ISL gestures have been considered as shown in Fig 1 under various light illumination conditions. One elementary approach for image processing tends to background uniformity where a dark background is chosen for dealing with gray scale images effectively.

To have a controlled environment, the background uniformity has been kept while recording the videos in real time. This will reduce the computational complexity during background removal and increase recognition accuracy in real time [15]. A single gesture video has been restricted to 30 frames. This is done by selecting 30 frames equally spaced in time from the original captured video. The background is chosen dark. Every ISL gesture implies some class or word which could be captured by waving both hands in a very appropriate manner [16]. For the enhancement of preprocessing ISL gestures need fast and accurate movements of hands. Several operations have been accomplished in all the ISL videos before the classification process. We have chosen those 5 ISL gestures for classification which can be easily imitated by HOAP-2 (please see Fig 1.).

IV. PREPROCESSING AND FEATURE EXTRACTION

Primarily, all the ISL videos are split up into sequences of image frames (RGB). The frames are converted into grayscale images and the background is subtracted in order to reduce computational complexity. The feature extraction for hand gesture recognition is done using orientation histogram [17].

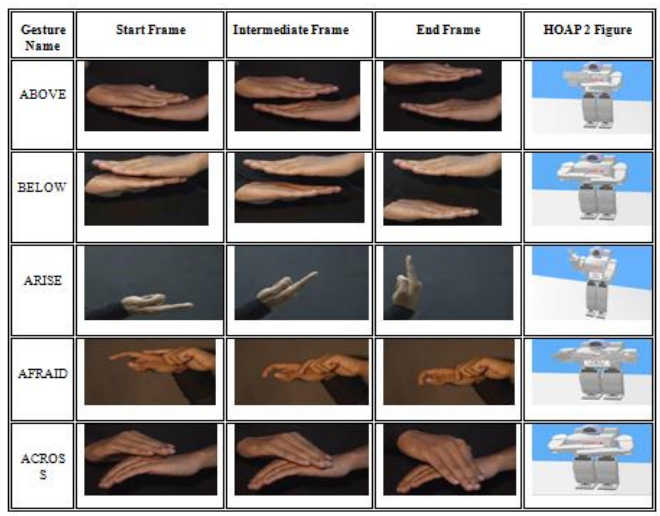

Fig 1: ISL gestures under different light illumination condition

As the name suggests it represents the angle information in the form of histogram according to the rules of frequency of occurrences. It provides tremendous flexibility towards scene illumination invariance property. Orientation histogram provides the local orientations of edges in sequence of images. The classification policy includes robustness in changing the illumination conditions. The histogram of dynamic gestures forms the feature vector based on the image intensity in spatio-temporal gradients.

Orientation Histogram demonstrates a very robust and efficient algorithm which would be used to classify ISL dynamic gestures based on the pattern classification technique. The algorithm is constituted with the histogram of the local orientation of edges in an image. The orientation histogram will be treated as feature vector for motion classification of ISL gestures. The algorithm is very fast and strong to compute the feature vectors of the sequence of images. Therefore, the calculation of direction of edges can be performed in real time applications.

It offers advantage to scene illumination changes and even light condition changes. The edges of the sequences of images would be still same [18]. All the ISL gestures have been captured in different lighting conditions. Another advantage of orientation histogram refers to the translation invariant property. It demonstrates that the same frames at different position of gestures would produce the same feature vectors. It is being done to calculate the histogram of the local orientations for all the frames of the moving gestures. Translation of the frame in the gesture does not change the local orientation histogram. The overall algorithm [21, 22] has been described to evaluate the feature vector for recognition system.

In our earlier work [19] & [20] we have plotted the orientation histogram of a particular gesture. It was landed up in the range of $-\pi/2$ to $\pi/2$, which is first and forth quadrants, and essentially neglects the second and third quadrants in order to speed up the computation.

V. ISL RECOGNITION TECHNIQUE

The classification process is done by two statistical techniques: HMM technique and Bhattacharya distance estimation.

Hidden Markov Model technique is followed by vector quantization technique with Linde Buzo Gray algorithm [22]. The HMM explains the construction of model which is needed to generate the observation sequences. Here we use a left-right HMM. The details of HMM is defined in the following manner [21]: In our researck work we have generated 5 different HMM models for 5 different ISL gestures for classification .

Three basic problems [21] are associated with Hidden Markov Model known as: *Evaluation Problem, Decoding Problem and Learning Problem*. These problems are to be solved for the models in order to implement them in the real world applications.

- *Evaluation Problem:*

This problem illustrates that a model $\lambda = (A, B, \pi)$ and observation sequences $O = O_1\ O_2 \ldots O_T$ are given and we have to efficiently compute $P(O|\lambda)$ where P denotes the probability of N observation sequence with the given hmm. This problem is being solved by well known Forward algorithm technique.

- *Decoding Problem:*

This problem illustrates that given a model $\lambda = (A, B, \pi)$ and observation sequences $O = O_1\ O_2 \ldots O_T$ we have to determine the corresponding state sequence $Q = q_1 q_2 \ldots q_T$ which refers to the most probable state path to obtain the given observation sequences. This problem is being solved by well known Viterbi algorithm.

- *Learning Problem:*

The model $\lambda = (A, B, \pi)$ is given and we have to adjust the model parameters in order to maximize the $P(O|\lambda)$. BaumWelch algorithm is being used in this problem.

The HMM based approach has been implemented to construct a real time, recognition based system for mimicry of ISL gestures. Each gesture is being represented as an individual model depicted in fig 3. The recognition of each gesture is done by calculating the maximum likelihood probability.

Bhattacharyya Distance Technique:

Another well known statistical approach known as Bhattacharyya distance (B_{Dist}) has been applied for recognition purpose of ISL gestures [24], [25] and [26]. It is extremely rich in its mathematical formulation and has been observed to give excellent result on statistical pattern classification. B_{Dist} is derived from Mahalanobis distance (M_{Dist}) which measures distance between two Gaussian distributions. B_{Dist} provides a weighted distance finding, where the weights are found from the covariance matrix and the mean vector of the two Gaussian distributions. B_{Dist} is therefore preferred to M_{Dist} , which provides a better measurement of separability between two classes estimated by class means and class covariance matrices. It is computationally very simple and extends to deal with more Gaussian mixtures. Bhattacharyya Distance $B_{Dist}(i)$ between the test gesture and the i[th] training gesture is computed by;

$$B_{Dist}(i) = [mean1 - mean2(i)]^T [\frac{cov1 + cov2(i)}{2}]^{-1} [mean1 - mean2(i)] + \frac{1}{2}\ln[\frac{\left|\frac{1}{2}[cov1 + cov2(i)]\right|}{\sqrt{|cov1\,||cov2(i)|}}]$$

Where, $mean1$ and $cov1$ are the mean and covariance matrix of test gesture accordingly. And $mean2(i)$ and $cov2(i)$ are the mean and covariance matrix of i[th] training gesture.

VI. VECTOR QUANTIZATION TECHNIQUE

A discrete HMM is taken into consideration for recognition process of ISL gestures. The feature vector of orientation histograms needs to be converted into a finite set of symbols from a codebook. The VQ technique plays a reference role in HMM based approach in order to convert continuous ISL gestural signals into a discrete sequence of symbols for discrete HMM. The VQ concept is entirely determined by a codeword which is composed by fixed prototype vectors. Fig 2 shows that the process of quantization has been divided into two parts.

The first part is having the ability to produce a codebook and the second part attempts to update the codeword followed by training of all the vectors according to their finite vectors. Its strength lies in reducing the data redundancy and the distortion created among the quantized data and the original data.

It is essentially required to propose a VQ method which would be genuinely used to minimize this distortion measure. In order to compute the minimum average distortion measure for a set of vectors an iterative algorithm is proposed by Linde, Buzo and Gray [22] which is known as LBG vector quantization designing algorithm. The algorithm illustrates the generation of optimal codebook (in our case codebook size is 16) for isolated ISL gestures.

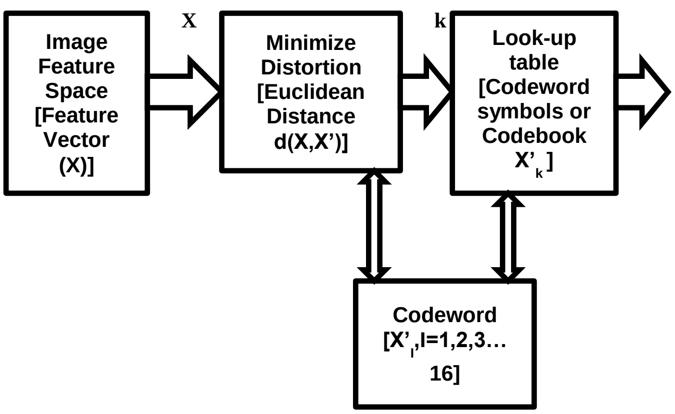

Fig 2: Vector Quantization process for codebook generation

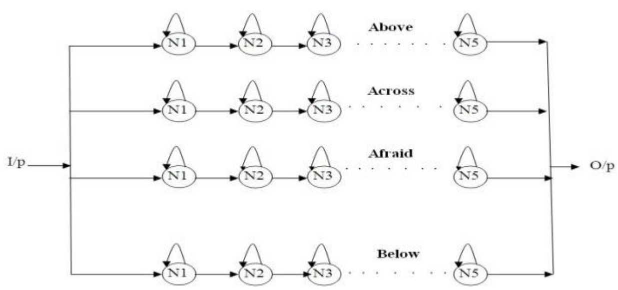

Fig 3: Parallel HMM recognition model for each gesture

VII. PERFORM IMITATION BY HUMANOID ROBOT

An underlying concept of learning gestures has been introduced for humanoid robot HOAP-2 (Humanoid Open Architecture Platform 2) in order to perform several tasks eventually [27]. An integration of humanoid robot with ISL gestures encounters an elegant way of communication through mimicry. The real time robotics simulation software, WEBOTS is adopted to generate HOAP-2 actions accurately. The way of learning process marks an intelligent behavior of HOAP-2 which sustains its learning capability in any type of environment. The learning process is dealt with the HOAP-2 robot controller which has been built intelligently. It is used to invoke Comma Separated Value (CSV) file in order to perform that gestures in real time. All the classified gestures bring out some useful information about all the joints of upper body of the humanoid robot.

Learning ISL gesture using HMM with vector quantization techniques:

In order to learn the ISL gestures by humanoid robot the preprocessing technique is essentially needed for this purpose. It employs the following steps.

- Capture the ISL gesture as an input gesture.
- Apply an algorithm for extracting orientation histogram to construct feature vector.
- From the feature vector of each gesture an initial codebook is to be generated. Then apply LBG algorithm to generate an optimized codebook.
- Each row corresponds to a number of the codeword which helps to form a quantized vector used by hmm algorithm.

In this preprocessing step we have generated 30 symbol sequences for each ISL gesture as each gesture is captured with equal number of frames.

Next stage implies to train each gesture using Hidden Markov Model where parameters of the HMM can be determined efficiently. We calculated the transition probability and emission probability of HMM by the known states and known sequences. The training algorithm for each gesture measures the accurate transition and emission probability which are used for finding out the most probable sequence.

It has been assumed 5 hidden states for each ISL gesture and made the state sequences in the distribution of 1 to 5 with total number sequence matches the codebook size. The observation sequence for each state has been represented by row vector with the calculated codebook of all the training samples. Each observation sequence for each training gesture corresponds to single row vector. Then apply algorithm for the estimation of transition and emission probability of each gesture model and preserve it for recognition purpose with unknown gesture.

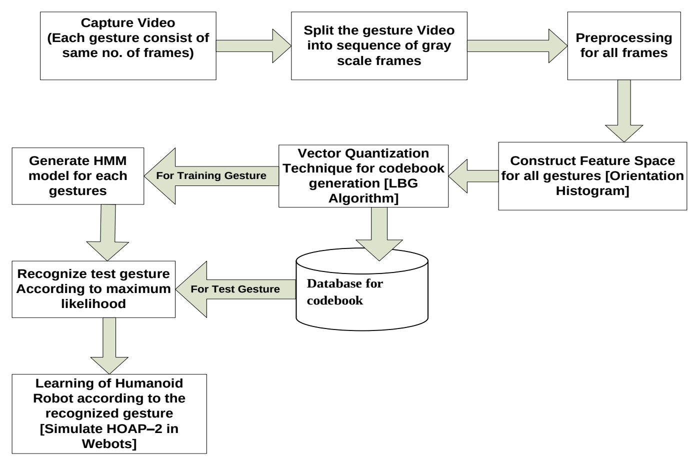

Fig 4(a): Learning of ISL gesture using HMM technique

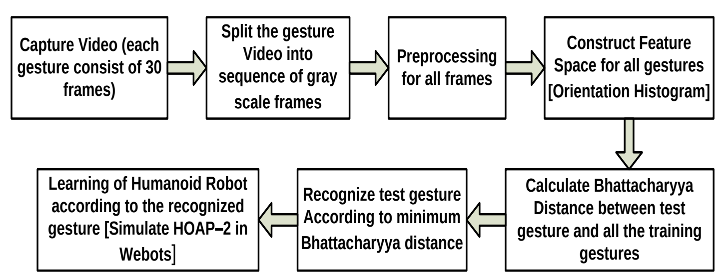

Fig 4(b): Learning of ISL gesture using Bhattacharyya Distance Technique

Every HMM model is uniquely attached with each gesture which is trained with different samples of each ISL gesture.

This trained model is extensively used for recognition of new gesture. This new gesture would be tested through all the trained HMM model. The new gesture is to be declared as classified when it provided a maximum likelihood state with a trained gesture.

Compute the percentage of each probable state for all the training samples which agrees with the likely state sequences of test gesture. The gesture is declared as classified with maximum percentage.

Learning ISL gesture using Bhattacharyya distance techniques:

In the other method, the Bhattacharyya Distance ($B_{Dist}(i)$) is computed between the test gesture and all the training gesture. Wherever $B_{Dist}(i)$ is found minimum with the training gesture, it is declared as classified.

Each of these training gestures has been mapped with a unique CSV action file for the humanoid robot. As soon as a gesture is classified, the mapped CSV file is invoked on HOAP-2 in a mimicry model. In Fig 4(a) and Fig 4(b), it has been shown that the entire process of recognition and then learning of classified ISL gesture has been achieved by HMM based technique and Bhattacharyya Distance based technique in real time.

VIII. RESULT ANALYSIS

In this paper we are only concentrating on those gestures which can be performed by humanoid robot HOAP-2 on WEBOTS simulation platform. Only 5 ISL gestures are selected for our work. In our work the same gesture is performed by the three different persons. During acquisition of ISL video gestures we have kept same number of frames for each gesture. It makes the recognition process easier but it reduces the freedom of doing the gesture. In the HMM classification process each model is tested by Viterbi algorithm, where same number of frames are required to get percentage of the matching gesture.

We have taken 7 samples of each gesture for training and 3 separate samples for each gesture for testing. We have generated probable path from the trained hidden model for each training samples of each gesture using viterbi algorithm. The same process is also applied for test samples of each gesture. In the recognition phase of known gestures, we have taken test sample one by one from the test gestures and have compared that sample with all the samples of each trained gestures iteratively. It produces the recognition percentage of that particular sample into the entire training samples. In that process we have created separate training set and test set with most probable paths. If a particular gesture is matched with 60% and above according to the maximum likelihood state with one of the training samples of that gesture then it is considered as classified gesture. We have achieved up to 100% recognition accuracy with both the techniques.

An efficient HRI system can be made by calculating the time taken by classification of ISL gestures in real time. We have seen that Bhattacharya distance technique is more efficient than HMM technique in accordance with taking minimum time for classification. The X axis represents the gesture index which refers to the samples of ISL test class whereas Y axis expresses the exact time is being taken by each gesture for classification in real time.

Fig 5: Time taken to recognize the ISL gesture in real time

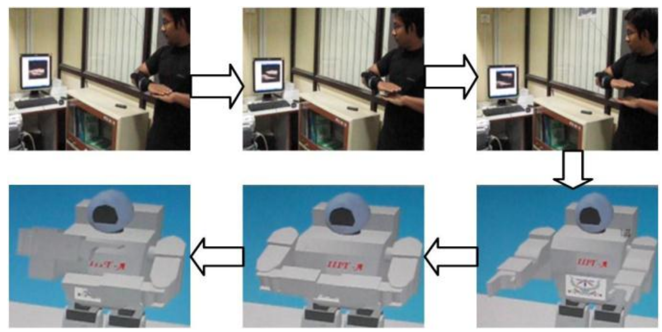

Fig 6: Real time imitation based learning on HOAP-2 robot

The Fig 5 shows the time taken to classify the ISL gesture through HMM (red line) and B_{Dist} (blue line). The total prototype is tested and simulated on Intel Core 2 Duo system with Matlab coding. It has been observed that the HMM based approach takes more time than the B_{Dist} based technique. This is because HMM based approach has the overhead of codebook generation. We therefore can conclude that this novel technique in gesture classification using B_{Dist} is efficient and can be implemented in real time, if the no of gestures is limited.

Each gesture for mimicry generation needs a special care of its dedicated joints which are responsible to perform that gesture. Each time the Comma Separated Value (CSV) file is constructed keeping only variation of responsible joint angle values of that gesture. Fig 6 shows the gesture generation and imitating that gesture on humanoid robot HOAP-2 in real time. The proper calibration and zero correction of respective joints of humanoid robot have been accomplished before imitation.

IX. CONCLUSION AND FUTURE WORK

In this work we have used ISL gesture as a communicating agent between human and robot interaction. This is our first step to design a prototype of vision base HRI system for speech and hearing impaired persons. They can use the humanoid robot as his translator or as his helping agent where the persons could communicate with the robot through ISL gesture. According to the observation we select Bhattacharyya Distance as a best recognition tool compatible with orientation histogram according to time taken and accuracy for recognizing the gesture the gestures. However in the present work we are only implementing a mimicry action by the humanoid robot. We could in principle use these techniques for trying to recognize any other human gestures. However the complexity of classification will increase because of the ambiguity in normal human gestures. We have chosen ISL because of its rigid vocabulary which makes the classification simpler. The present work only recognizes a single gesture at a time. It will be challenging to recognize multiple gestures or sequence of gesture one after the other. The task in hand will be to separate out each gesture from the sequence of gestures and use our gesture recognition techniques as described in this paper.

ACKNOWLEDGMENT

This research work was funded by Indian Institute of Information Technology, Allahabad, India.

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