Review in Sign Language Recognition Systems

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***Abstract*—The Sign Language Recognition System (SLR) is highly desired due to its ability to overcome the barrier between deaf and hearing people. At present, a robust SLR is still unavailable in the real world due to numerous obstacles. Additionally, as we know, Sign Language recognition has emerged as one of the most important research areas in the field of human computer interaction (HCI). Hence, this paper presents an overview of the main research works based on the Sign Language recognition system, and the developed system classified into the sign capturing method and recognition techniques is discussed. The strengths and disadvantages that contribute to the system functioning perfectly or otherwise will be highlighted by invoking major problems associated with the developed systems. Next, a novel method for designing SLR system based on combining EMG sensors with a data glove is proposed. This method is based on electromyography signals recorded from hands muscles for allocating word boundaries for streams of words in continuous SLR. The proposed system is expected to resolve words segmentation problem, which will contribute to enhanced recognition capability for the continuous sign recognition system.**

Keywords-components: **ASR, Data-glove, EMG, ANN, HMM**

I. INTRODUCTION

Sign Language is a gesture language which visually transmits sign patterns using hand-shapes, orientation and movements of the hands, arms or body, facial expressions and lip-patterns to convey word meanings instead of acoustic sound patterns. Different sign languages exist around the world, each with its own vocabulary and gestures. Some examples are ASL (American Sign Language), GSL (German Sign Language), BSL (British Sign Language), and so on. This language is commonly used in deaf communities, including interpreters, friends, and families of the deaf, as well as people who are hard of hearing themselves. However, these languages are not commonly known outside of these communities, and therefore communication barriers exist between deaf and hearing people.

sign language communication is multimodal, it involves not only hand gestures (i.e. manual signing) but also non-manual signals. Gestures in sign language are defined as specific patterns or movements of the hands, face or body to make out expressions. However, in this paper only manual signing is concerned.

Hand posture is defined as a specific shape of hand flexion at an instantaneous time, while a hand gesture is defined as a consequence of posture during a time domain. In this paper the term “gesture” refers to a hand gesture which is also mentioned as a sign or word.

Over the last decade many works of research have been directed toward developing a sign recognition system for different sign languages [10-20] and it was concluded that such a system is challenging for various disciplines including gestures capturing method, machine learning classifiers, human action understanding, and natural language processing. Unfortunately, most introduced systems for sign recognition are addressed as isolated systems where each gesture is fed separately to be recognized. A continuous sign language recognition system is defined as a translation of a gesture “phrase” stream to opposite meaningful speech or text. It is more interesting than isolated because true human signs are continuous and any isolation arising will affect communication flow [1]. The complexity in the sign recognition system arises from the fact that sign languages are the least identical, with large vocabularies and referential language, in contrast to voice languages whose features include co-articulation of several human body signals, thus making the task of recognizing isolated or continuous signing highly multifaceted. Recently, several approaches of sign recognition have been proposed; however, efficient automatic sign language system recognition still remains an open problem.

The structure of this paper encompasses an overview of sign capturing methods and gesture classifying techniques successfully used so far, followed by a review of the problems with the continuous sign recognition system. Then, the author introduces the continuous sign recognition system for Bahasa Isyrat Malaysia (BIM).

II. SIGN CAPTURING METHOD

1. Vision-based sign extraction

Vision-based methods are widely deployed for Sign Language recognition. In these methods, sign gestures are captured by a fixed camera in front of signers. The extracted images convey posture, location and motion features of the fingers, palms and face. Next, an image processing step is required in which each video frame is processed in order to isolate the signer's hands from other objects in the background.

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The image extracting methods have the advantage of extracting face and body gestures of the signer; however, it is commonly associated with image noises delivered from many sources (camera, light, color matching, and background). Some researchers have applied an error filter to reconstruct the damaged parts [2], but the problem is that errors relate to a dynamic environment. Also, the vast computation needed is another issue with a real time vision system. For example, Nielsen et al. [3] suggested a real time vision system that uses a fast segmentation method, by using minimum features to identify hand posture in order to speed up the recognition process. However, this method loses major hand features and results in bad recognition accuracy. Overlapping is another problem that occurs when a hand hides behind another body part, as seen in Figure (1). Helen, et al [4] used camera mounted above the signer, so the images captured by this camera clearly solve the overlapping between the signer's hands and head. On the other hand, face and body gestures are lost this way.

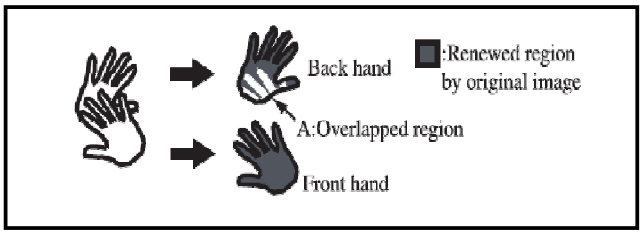

Figure 1. Overlapping issue in the image extracting method [16]

2. Data-Glove

Data-gloves are special gloves consist of strain gauge and hand tracker. The strain gauge sensor used for detecting Hand and finger bend. The hand tracker is an electronic device provides the location, orientation, velocity and direction of hand according to a fixed reference. Data-glove gesture interaction achieves good performance especially for sign capturing in SLR with high reliability and the elimination of the pre-processing stage. The main drawback of using data-glove is that the user needs to wear gloves, which potentially hindering convenience and natural movements. Non manual gestures are also neglected in this method.

3. EMG (electromyography)

Electromyography (EMG) sensor measures the electrical potential signal generated by muscle cells, and records it using differential pairs of surface electrodes. EMG has been successfully used in control command for prosthetic limbs and virtual games. The feasibility of using EMG signals for gesture recognition is due to the fact that different movements indicate different EMG muscle signatures [5]. Recently, EMG has shown interesting results in hand pattern recognition using EMG signals. For example Kyung Kown et al. [6] introduced a method of classifying 6 hand gestures in Korean Sign Language. Yi-Chun Du et al. [7] used 7 surface-mounted electrodes to recognize 11 hand gestures. On the other hand, EMG contains complex types of noise caused by equipment and the interaction among various tissues and muscles [8]. Also, feature extraction and the signal processing needed are quite complex and vary from subject to subject. Nevertheless, even though this method is somewhat new, it has been successfully utilized for recognizing a limited number of hand postures for control purposes and is still far from being a capturing system for sign language recognition.

III. GUSTURE CLASSFIER

1. Artificial neural network approach

An artificial neural network consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. Many researchers highlight the success of using neural networks in sign language recognition. The biggest advantage of the neural network method is its generality . also it reflects the ability to learn relationships directly from modeled data while at the same time meeting real-time recognition constraints [9]. Different network models exist for training the neural net for ASR , of which the most widely chosen are Back Propagation, Multilayer Perceptron (MLP), and Simple Recurrent Networks (SRN-Elman and Jordan networks).

Yasir Niaz et al. [10] introduced the ANN system for the ASL alphabet gesture recognition. Three-layer ANN is used where inputs layer contain 7 neurons engaged from the data glove sensors. Outputs layer contain 26 neurons, each representing a letter. Feed forward algorithm is used to calculate the output for a specific input pattern. Back propagation algorithm is also used for learning the network. The system uses four samples per minute and the user must perform the sign for $3/4_{th}$ of a second to have it recognized. Results showed an 88% recognition rate of static gestures. The major weakness was that only static gestures can be recognized, therefore many letters were omitted from the test domain because they involve dynamic gestures.

Machacona et al. [12] used a Multilayer Perceptron (MLP) neural network to recognize static hand-finger gestures of the yubimoji, (Japanese Sign Language syllabary). Signal inputs from the data glove interface were taken for each static yubimoji gesture separately. Each input was fed as input of MLP, after which the network was trained 10 times and tested for 41 gestures. Generally, only 18 of the static gestures were successfully recognized. One of the reasons was attributed to the data glove's inability to measure gesture directions, particularly yubimoji gestures with similar finger configurations.

Ali Karami et al. [11] presented a system for recognizing static gestures of Persian sign language (PSL) alphabets. The system consists of two phases: the feature extraction phase and the classification phase. DWT is applied to the images of bare hands, then, inputs are extracted using some features from the image's wavelet coefficients. The coefficient matrices are obtained from the sub-images of the

6th, 7th or higher levels of the wavelet decomposition tree and used as the NN inputs. The MLP NN architecture was used with 52 input nodes, one hidden layer with 10 neurons, and 3 linear output neurons was chosen based on a trial-and-error process. Then, a set of 32 PSL alphabets was selected for testing and a classification accuracy of 98% was obtained.

Another work was also introduced by sole et al. [13] to classify South African Sign Language (SASL) using Extreme Learning Machine (ELM) by expanding the input data into a higher dimensional space using randomly allocated sigmoidal basis functions. The training target vector is approximated by a linear weighted sum of these basis functions. These hidden sigmoidal units are drawn from a uniform random distribution. The hidden weights do not get tuned, hence, many are needed (typically <100). As a matter of fact, ELM offers very fast learning as it does not use any gradient-based learning algorithms. The only tuning parameter is the uncritical number of hidden neurons. The system architecture is built with 14 inputs from the data glove and 26 outputs of which each represents letters of the alphabet. Results were tested at a 200 dimensional space ELM and showed the ability to classify individual letters of the alphabet with an accuracy of up to 95%.

Vamplew et al. [14] developed a system for Australian Sign Language (Auslan). The model is based on a neural network technique using a hand glove and magnetic tracker for extracting data. The signs captured were then classified into four feature vectors named hand-shape, location, orientation and motion. Different from other works, a temporal neural network was used for the hand motion feature which has the ability to process input patterns that change over time. Three classification levels were obtained, namely spatial features, temporal features and whole sign classification. Different neural network architecture was used for each level and vector. For example, a 16:4:30 architecture was used for hand-shape classification and trained using instant-based learning (IBL) methods, while ten networks with a 8:8:13 recurrent architecture were trained with a pre-processing method used for hand motion classifications. Besides, the nearest-neighbor algorithm was used as a final sign classifier using a heuristic distance measure (HDM), derived by examining the confusion matrices of the 7 feature-extraction networks on the training examples. Results showed that SLARTI has the ability to recognize 52 words in the Auslan language with an accuracy rate around 94%, based on 6 different signers in training. The major advantages of this work include its aptitude to classify dynamic gestures, while a weakness consists of the independent vector classification feature, whereas co-dependency is present among these sign features such as hand shape and orientation.

1) Hidden Markov Model (HMM)

HMM is a statistical model capable of modeling spatio-temporal time series. An HMM has a finite set of states governed by a set of transition probabilities. In a particular state, an outcome or observation can be generated according to an associated probability distribution. HMM is used in robot movement, bioinformatics, speech and gesture recognition. This model has two advantages regarding sign recognition, the ability to model linguistics roles and its ability to classify continuous gestures within a certain assumption [15].

Tanibata et al. [16] developed an isolated recognition system for JSL by applying HMMs which model gesture data from the right and left hands in a parallel mode using the Baum-Welch algorithm. The probability of each sequence using each HMM of one word was then obtained. The Viterbi algorithm was used to manually verify whether sample transitions occur around sign borders. Distinguishing between words similar to the beginning parts of other words was done by confirming whether they reach the final state of HMM. During the test 65 JSL words were used and results show that the method could recognize 64 out of the 65 words.

Liang et al. [17] developed a continuous system for the Taiwanese Sign Language using a Data-glove. Two HMM models were developed. The gesture model which includes a lexicon for matching recognized gestures consists of four sub-models of the left-right hidden Markov, namely Posture, Position, Orientation and Motion. The other was the language model which includes grammar and semantics for matching sentences and phrases. The goal of the grammar model is to provide an estimate of the probability of a gesture sequence, which could improve recognition rate. Results presented 84% recognition rates when using 71 words and 70% when using 250 words.

Jiyong and Wen [18] developed a real-time system designed to recognize continuous Chinese Sign Language (CSL). Raw data was collected from two Cyber-Gloves and a 3-D tracker. Dynamic programming (DP) technique was used to segment the training sentence into basic units, then, re-estimating was done by the Welch-Baum algorithm. The worked data was presented as input to the Hidden Markov Models (HMMs) for recognition. 220 words and 80 sentences were used in the test and the system showed 94.7% recognition rates.

Ramamoorthy et al. [19] employed an HMM based on real time dynamic gesture recognition system which uses both the gesture's temporal and shape characteristics for recognition. They developed a recognition engine which can reliably recognize these gestures despite individual variations. The recognition strategy uses a combination of static shape recognitions (performed using contour discriminant analysis), Kalman filter-based hand tracking and an HMM-based temporal characterization scheme. Use of both hand shape and motion pattern is a novel feature of this work.

Voglar et al. [20] developed Parallel Hidden Markov models (PaHMMs) for American Sign Language recognition. Two channels for the right and left hands were used, assuming any word can be broken down into fundamental phonemes the same as words in speech recognition. They stated that phonemes could be used instead of whole signs for a continuous recognition system. A single channel of the HMM model was tested for a small vocabulary number (22 signs) with results showing an 87.88% accuracy rate.

Bowden et al. [21] developed a system for recognizing British Sign Language (BSL) which captures data using an image technique then extracts a feature set describing the location, motion and shape of the hands based on BSL sign linguistics. The recognition is performed using Markov chains in combination with Independent Component Analysis (ICA). High level linguistic features were used to reduce the recognizer's training work. The recognition rate achieved was 97.67% for a lexicon of 43 words using single instance training.

IV. PROPLEMS WITH THE CONTINUOUS SIGN RECOGNITION SYSTEM

Continuous sign recognition refers to the recognition of phrases or sentences. Its complexity arises from dealing with a stream of gestures not physically separated by discontinuity such as speech words. Many researchers have addressed this challenge and tried to overcome this limitation.

Phoneme modeling is one of the several methods used for continuous recognition. It can be achieved making the assumption that signs can be broken down into several smaller units called phonemes or chremes [20] which can be segmented based on the change in the movement's direction or hand location. Then phonemes are modeled in a single channel using HMM more like speech. This model has fundamental weaknesses in that it varies from spoken language where phonemes appear in sequences, while in sign language appear in both sequences and parallel to sign language due to language articulation [23]. Also, there are about 50~60 phonemes in spoken language, while in sign language there are about 2500~3000 because there is no exact definition of phoneme in sign language [17].

Another technique uses isolated recognition as a step after the continuous one. This method proves most attractive for two main reasons; the first being that recognizing full sentences in sign language depends strongly on linguistic modeling of the sequential appearance of signs to form full meaningful sentences. The second reason is the vocabulary size in sign language dictionaries, where for example, ASL has more than 6000 signs. Hence, the number of statements which can be formed using 3-word combinations per statements is very large and difficult to convey by the continuous recognition system.

Tanibata et al. [16] proposed a method for allocating signs in image sequences by supposing that any sign consists of a motion-pose-motion state. So, hand motion is important at high velocity, while hand shape is important when velocity is lower. Thus, the boundary between motion-pose states is detected when (1) is satisfied:

$$\begin{cases} V(t) \leq \Theta_V & \text{if } \bar{V} > \Theta_V \\ V(t) \geq \Theta_V & \text{if } \bar{V} < \Theta_V \end{cases}$$

$$V(t) = \sqrt{\begin{array}{l}\{x_{hand}(t) - x_{hand}(t-1)\}^2 \\ +\{y_{hand}(t) - y_{hand}(t-1)\}^2\end{array}}$$

where

Θ_V:threshold for the change of the hand velocity.

$\bar{V}$:the average velocity from $t-1$ to $t-|n$

The border between pose-motions is also detected when the hand motion direction changes drastically when (2) is satisfied:

$$\begin{array}{l} I(t) > \Theta_I \\ I(t) = |\theta_{motion}(t) - \theta_{motion}(t-1)| \end{array} \quad (2)$$

where

Θ_I:threshold for the change of the direction of the hand motion.

Mahmoud et al. [22] assumed that continuous gestures can be segmented by motion static velocity detection in a gesture stream. However, Liang et al. [16] introduced a time varying parameter (TVP), used to determine end points in a sequence of a gesture stream. Discontinuities are detected for segmentation whenever the number of hand flexion TVPs begins to fall below a threshold, the motion of posturing is thought to be quasi-stationary, and its corresponding data frame is taken to be recognized. Acceleration-based segmentation was also used by [23] who considered a strong relation between sign presentation and hand movement acceleration. Another method is to introduce physical separation using a contact switch triggered by the signer when a sign is finished. This switch is either cached by hand or pushed on a foot pedal [14]. Overall, the success of previous segmentation methods strongly depends on how the stream of gestures satisfies their pre-defined assumption.

Another issue with continuous recognition is movement epenthesis which appears as an extra movement between two sequential signs because the end and the start of two sings are mismatched in location [23, 16]. However, ignoring epenthesis will cause decreased recognition accuracy.

V. A CONTINUOUS SIGN RECOGNITION SYSTEM BASED ON EMG SEGMENTATION AND THE HIDDEN MARKOV] (1)

In this paper a system for continuous sign language recognition is introduced, and is presented at three levels: data acquisition, gesture recognition, and the language modeling level. The acquisition level comprises data collection based on data-glove. In order to overcome the previous work segmentation limitation, a multi-channel EMG sensor for gesture segmentation based on muscle activity monitoring during gesturing is introduced. This method was first presented by Zhang et al. [27] for the segmentation of hand gestures used in virtual game control. The idea behind using EMG signaling is that it presents the level of muscle activity which relates to an active gesture. A pilot study was implemented to check the feasibility of fusing EMG to detect gesture boundaries in a stream of gestures. Four EMG electrodes were placed on different palm muscles, namely the first dorsal interosseus medial slip, first dorsal interosseus lateral slip, opponens pollicis, and the abductor pollicis brevies (Fig. 2). Then signer is asked to perform two sequential gestures normally.

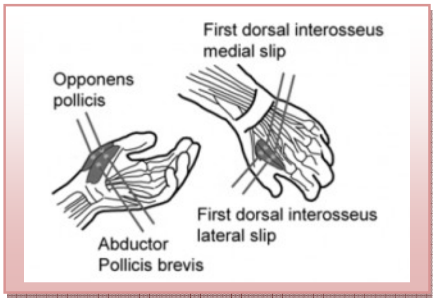

Figure 2. Surface mounted electrodes in hand palm

During gesturing when finger posture switches from one gesture to another one, the palm corresponding muscle shows relaxation for a while and EMG signal amplitude appears to be very low. To detect the boundaries of gesture, the multi-channel EMG signals are averaged using equation (1), then a moving average is calculated with a window size of W=100 sample size using equation (2). The threshold value is set and tested to be validated for a period of time (200ms) in order to eliminate rises and drops caused by noise (Figure 3).

$$AVG(t) = \sum_{c=1}^{4} EMG(t) \qquad (1)$$

$$MOV_{AVG}(t) = \frac{1}{W} \sum_{i=t-w+1}^{t} AVG^2(i) \qquad (2)$$

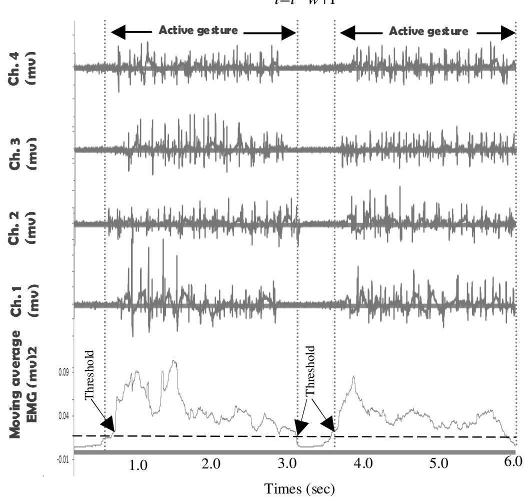

Figure 3. Threshold principle illustration

The second level is gesture recognition where a four-channel HMM is used to classify the gesture, and each channel presents one gesture articulation (movement channel, hand shape channel, orientation channel and rotation channel) based on the modeled lexicon. Sentence recognition level uses a single HMM channel to match a recognized gesture with a modeled sentence based on language grammar and semantics (Figure 4).

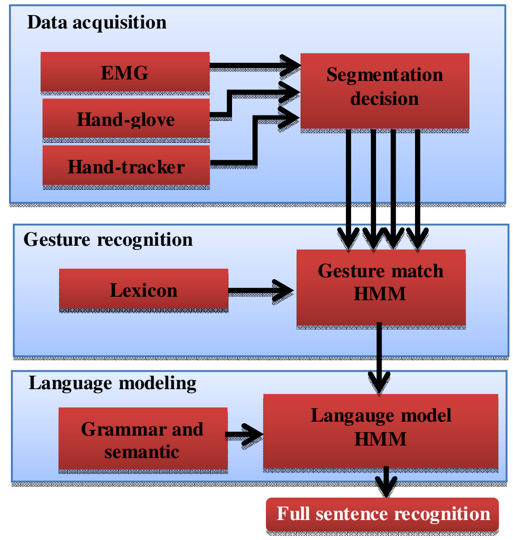

Figure 4. Overview of the proposed system

VI. CONCLUSION

The continuous sign language recognition system is highly desirable in communication practices with the deaf society. Image-based and hand glove-based methods associated with a hand tracker are the methods most used for capturing hand gestures in sign language. Using data-gloves enables more intricate gestures that involve moving individual fingers, wrist and hands, allowing for more flexible, accurate and reliable gesture recognition. However, the image-based method offers user-independent feature extraction, but needs more processing for feature extraction and noise reduction. On the contrary, it conveys face and body movements which provide more detailed sign gestures.

ANN neural networks presented robust behavior during gesture prediction because they did not saturate or get locked in oscillatory behaviors [9]. The downside of using ANN classifiers is the required training process as well as the training process needed for extending new vocabulary [13]. The Hidden Markov Model (HMM) classifier also proves interesting in sign recognition due its ability to model words based on sets of predefined states. However, its limitation lies in its dependency on the assumption that the distribution of individual observation can be presented using a mixture of Gaussian densities which is not always true [24]. HMM has been reported to provide poorer discrimination than neural networks [25] compared to HMM and ANN in sign language, which is still a matter of debate.

Most recognition results shown are based on the author's own collection of data and selected vocabulary, thus results will not fairly reflect the reliability of these systems. It seems to be interesting to set performance measures in sign recognition systems rather than report tested words' accuracy. Additionally, since true human gestures are continuous, introducing an isolated system can significantly disrupt the natural flow of human interaction and it does not have as much value in the reality of sign recognition. The success of a fully automated sign recognition system relies on solving current problems associated with continuous gesture recognition. Unfortunately, solving methods introduced depend on an underlying assumption which may satisfy a fixed condition or a number of gestures in a specific sign language. In another method classified as un-practical the signer must grip a contact-switch while performing the signs. As noted earlier, it has been concluded that if the input stream is not artificially segmented, the feasibility of developing a continuous recognition system for a large vocabulary is impossible.

VII. FUTURE WORK

More studies will be conducted to evaluate EMG segmentation for full sentences in sign language. Also, integrating EMG signals with hand velocity and positions will be considered for developing a segmentation method.

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