Vision-Based Sign Language Recognition Systems : A Review

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***Abstract*— Sign Language (SL) is a method of communication for deaf people and speech impaired. Sign language differs from country to country so it is not a standard and universal. Used sign language to the deaf community and speech impaired to communicate with normal people need to Sign Language Recognition (SLR). Automatic SLR basically uses two approaches based on computer vision (computer vision), and based on the sensor data. Computer vision-based gesture recognition, a camera is used as input. Videos are captured in the form of video files stored before being processed using image processing. Approach based on sensor data, is done by using a series of sensors that are integrated with gloves to get the motion features finger grooves and hand movements. In order to improve recognition accuracy, the researchers use methods such as Hidden Markov Model, Artificial Neural Network. Effective algorithms for segmentation, matching the classification, and pattern recognition have evolved. The main objective of this paper is to analyze the effective methods and compare them.**

Keywords: Sign Language Recognition, Hidden Markov Model, Artificial Neural Network.

I. INTRODUCTION

Communication is an important thing in life, which can be done many ways to communicate, such as by speaking through oral or sign language. Sign Language is a gesture language which visually transmits sign patterns using hand-shapes, orientation and movements of the hands, arms or body, facial xpressions 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 American Sign Language (ASL), Chines Sign Language (CSL), British Sign Language (BSL), Indonesian Sign Language (ISL) and so on.

Sign language is the basic alternative communication method between deaf people and several dictionaries of words or single letters have been defined to make this communication possible. Sign language used by the deaf and speech impaired is difficult to understand by the general public they feel ostracized by the surrounding environment.

Progress in the field of pattern recognition systems promises to the automatic sign language interpreter. Few research has been conducted in order to generate tools to help to translate sign language into text and or speech. Researchers in the field of sign language are categorized into two: a vision-based computer (computer vision), and based on the sensor data. Computer vision-based gesture recognition, a camera is used as input. Videos are captured in the form of video files stored before being processed using image processing. If the feature image using the 2D images using a camera as in [1], and for 3D, data takes more than a camera, as in [2] using eight cameras. The recognition pre done form the first image processing, such as segmentation and hand tracking. And there are problems such as noise, intensity differences, and occlusion.

Several works have been proposed previously, and they mostly make use of probabilistic models such as Hidden Markov Models and Artificial Neural Network. The main objective of this paper is to analyze the effective method and compare them.

The rest of this paper is organized as follows. Section 2 describes a review on sign language recognition system, including sign language, sign capturing methods, sign language recognition methods. Finally, the conclusion of this work is described in Section 3.

II. A REVIEW ON SIGN LANGUAGE RECOGNITION SYSTEM

A. Sign Language

The term sign language is similar to the language term, there are many of both spread in various territories of the world. Just like the language, sign language developed in a long time, has a sign language grammar and vocabulary, so it is considered a real language [3]. The difference between sign language and common language is on the method to communicate/articulate information. Because no sense of hearing is required to understand sign language and no voice is required to produce it, it is the common type of language among deaf people [4]. 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 American Sign Language (ASL), German Sign Language (GSL), British Sign Language (BSL), Indonesian Sign Language (ISL) 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 our expressions. Summarized by Boyes Braem the most important modern findings about sign language are as follows:

1) Sign language is a natural language that was not made up. Many deaf children acquire it as their mother tongue from other children at school or from their parents, which shows that the acquisition process is similar to that of spoken languages [3].

2) Since it is a natural language, sign language is closely linked to the culture of the deaf, which it originates from. Thus, knowledge about the culture is necessary to fully understand sign language.

3) As mentioned above, there is not just a single sign language worldwide, but many national variants. These national variants can even have regional dialects [3].

4) Unlike pantomime, sign language is not linked to iconic contents. Abstract thoughts can be expressed just as well as in spoken languages.

5) Furthermore, sign languages are not incomplete variants of languages spoken in the same region. Instead, they feature their own structure that can be completely different from that of the surrounding spoken languages.

B. Sign Capturing Methods

1) Data Gloves Approaches

These methods employ mechanical or optical sensors attached to a glove that transforms finger flexions into electrical signals to determine the hand posture [5]. As depicted in Figure 1, using this method the data is collected by one or more data-glove instruments, which have different measures for the joint angles of the hand and Degree Of Freedom (DOF) hat contain data position and orientation of the hand used for tracking the hand [6]. However, this method requires the glove must be worn and a wearisome device with a load of cables connected to the computer, which will hamper the naturalness of user-computer interaction [7].

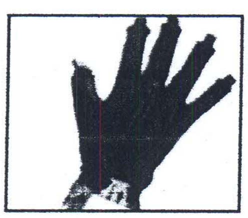

Fig. 1. Examples of the data glove

2) Vision-based sign extraction

These techniques based on the how a person realized information about the environment. These methods usually done by capturing the input image using the camera as depicted in Figure 2. In order to create the database for gesture system, the gestures should be selected with their relevant meaning, and each gesture may contain multi samples [8] for increasing the accuracy of the system.

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.

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 [9], but the problem is that errors relate to a dynamic environment. Furthermore, the vast computation needed is another issue with a real time vision system. For example, Nielsen *et al.* [10] 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. Helen, *et al* [11] 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.

Fig. 2. Examples of data vision based

3) Kinect-based (Microsoft Kinect XBOX 360TM)

Microsoft Kinect was initially developed as a peripheral device for use with the XBOX 360TM gaming console. Its three sensors, i.e. RGB, audio, and depth (Figure 3), enable it to detect movements, to identify user faces/speeches, and allow the players to play games using only their own body as the controller. In contrast to previous attempts at gesture or movement-based controls, there is no need of wearing accessories in order for the device to track the users. Although its initial goal was for gaming-purpose, Microsoft Kinect opened the door to a wide number of useful applications in the field of Computer Vision, such as Action Recognition, Gesture Recognition, Virtual Reality, and Robotics. Figure 3 describes the kinect diagram.

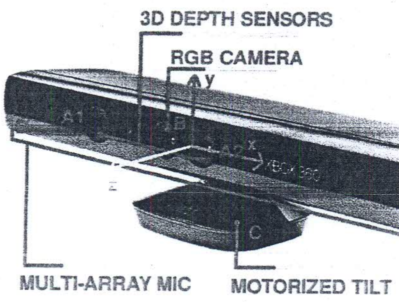

Fig. 3. Kinect Diagram

It features an RGB camera along with a microphone array and a depth sensor using an infrared projector, and is thus capable of tracking a user's full body independently from lighting of conditions. Kinect for XBOX 360™ is changing the game. Besides its application on Xbox 360, several drivers exist that allow Kinect to be used on PC and Mac. Driver OpenNI was released in December 2010 by PrimeSense, the manufacturer of Kinect's camera technology. It includes a feature-rich open source framework licensed under the GNU Lesser General Public License, version 3, and can be combined with closed source middleware called NITE for skeletal tracking and recognition of hand gestures [12, 13].

The framework [14] created as part of this work by Simon Lang was called Dragonfly- Draw gestures on the fly, and mainly consists of two classes that users could use in assimilation with their software. The Depth camera serves as an interface to OpenNI, i. e. it updates the camera image and reports the data of the skeleton joints of the body parts, and the latter processes the data set for recognition.

III. Sign Language Recognition Methods

A. Hidden Markov Model (HMM)

HMM is defined as a set of states of which one state is the initial state, a set of output symbols, and a set of state transitions. Each state transition is represented by the state from which the transition starts, the state to which transition moves, the output symbol generated, and the probability that the transition is taken [15]. HMM is used in robot movement, bioinformatics, speech and gesture recognition. This model has two advantages regarding sign recognition, the ability to model linguistic's roles and its ability to classify continuous gestures within a certain assumption [16].

Liang *et al.* [17] used Two HMM models for a continuous system for the Taiwanese Sign Language using a Data-glove. And language model includes grammar and semantics for matching sentences and phrases. The purpose of the model of grammar is to provide estimates of the probability of a sequence of movements, which can increase the recognition rate. The test results are 84% recognition rates when using 71 words and 70% when using 250 words.

Jiong *et al.* [18] presented as input to the Hidden Markov Models (HMMs) for 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; Estimating was done by the Welch-Baum algorithm. Test results using 220 words and 80 sentences, and the system showed 94.7% recognition rates.

Feng Jiang [19] presents the Multilayer architecture in Sign Language Recognition for the signer-independent CSL recognition, where classical DTW and HMM are combined within an initiative scheme. In the two-stage hierarchy, they define the confusion sets and introduce DTW/ISODATA algorithm as the solution to build confusion sets in the vocabulary space. The experiments show that the Multilayer architecture in Sign Language Recognition increases the average recognition time by 94.2% and the recognition accuracy 4.66% more than the HMM-based recognition method.

Lang *et al.* [4] used hidden Markov models for Sign language Recognition Using kinect. The framework makes use of Kinect, a depth camera developed by Microsoft and PrimeSense, which features easy extraction of important body parts. The framework also offers an easy way of initializing and training new gestures or signs by performing them several times in front of the camera. Results show a recognition rate of > 97% for eight out of nine signs when they are trained by more than one person.

Tani Bata *et al.* [20] used HMMs for isolated for JSL recognition system, which models the data signals from the left and right hands in parallel mode using the Baum-Welch algorithm. For each sequence using HMM of one word was then obtained. Viterbi algorithm is used to manually verify whether a sample transition occurs around the border of the sign. Distinguish between words that are similar to the beginning of another word done to confirm whether they reach the final state of the HMM. During testing using 65 words JSL with results showing that the method can identify 64 out of 65 words.

Bowden *et al.* [21] used Markov chains in combination with Independent Component Analysis (ICA) for 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. High level linguistic features were used to reduce the recognizer's training work. The classification rates as high as 97.67% for a lexicon of 43 words using only single instance training. Volger [22] used Parallel Hidden Markov models (PaHMMs) for American Sign Language recognition. They stated that phonemes could be used instead of whole signs for a continuous recognition system. Used Two channels to the right and left hands, assuming any word can be broken down into fundamental phonemes the same as words in speech recognition. A single channel of the HMM model was tested for a small vocabulary number (22 signs) with results showing an 87.88% accuracy rate.

B. Artificial Neural Networks (ANN)

Many researchers highlight the success of using neural networks in sign language recognition. An Artificial Neural

Network (ANN) consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. The biggest advantage of the neural network method is its generality. Furthermore, it reflects the ability to learn relationships directly from modeled data while at the same time meeting real-time recognition constraints [23].

Shiga [24] 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.

Manar [25] used two recurrent neural networks architectures for static hand gesture to recognize Arabic Sign Language (ArSL). Elman (partially) recurrent neural networks and fully recurrent neural networks have been used. Digital camera and a colored glove were used for input image data. For segmentation process, *HIS* color model was used. Segmentation divides the image into six color layers, five for fingertips, and one for the wrist. Thirty features are extracted and grouped to represent a single image, expressed the fingertips and the wrist with angles and distances between them. This input features vector is the input to both neural networks systems. 900 colored images were used for training set, and 300 coloured images for testing purposes. Results showed that fully recurrent neural network system (with recognition rate 95.11%) better than the Elman neural network (89.67%).

Kouichi [26] presented Japanese sign language recognition using two different neural network systems. Back Propagation algorithm was used for learning postures of Japanese alphabet. For input postures, data glove was used. Normalization was applied for images as preprocessing step. The features extracted from data glove's image was 13 data items, ten for bending, and three for angles in the coordinates. The output of the network was 42 characters. The network consists of three layers, input layer with 13 nodes, hidden layer with 100 nodes, and output layer with 42 nodes, which corresponds with 42 recognized characters. The recognition rate for learning 42 taught patterns was 71.4%, and for unregistered people 47.8%, while the rate improved when additional patterns added to the system, it became 98.0% for registered, and 77.0% unregistered people.

Tin Hninn [27] used real time 2D hand tracking to recognize hand gestures for Myanmar Alphabet Language. Digitized photograph's images were used as input images, and applied Adobe Photoshop filter for finding the edges of the image. By employing histograms of local of orientation, this orientation histogram was used as a feature vector. The feature vector would be the input to the supervised neural networks system. MATLAB toolbox has been used for system implementation.

Gonzalo *et al.* [28] presented Continuous Time Recurrent Neural Networks (CTRNN) real time hand gesture recognition system. By using tri-axial accelerometer sensor and wireless mouse to capture the 8 gestures used. The work based on the idea of creating specialized signal predictors for each gesture class [28], standard Genetic algorithm (GA) was used to represent the neuron parameters. Each genetic string represents the parameter of a CTRNN. Two considered datasets have been applied one for isolated gestures, with recognition rate 98%for training set, and 94% for testing set. The second dataset for captured gestures in real environment, for the first set, with 80.5% for training, and 63.6% for testing.

Stergiopoulou [29] conducted a study on the static hand gesture recognition based Neural Gas Self-Growing and Self-Organized (SGONG) network. An input image using a digital camera. For the detection of the hand area of YCbCr color space is applied, and the threshold technique is used to detect skin tones. SGONG network using the competitive Hebbian learning algorithm, began studying with two neurons, and neurons grow where the grid will detect the exact shape of the hand. Specified number of fingers raised, but in some cases the algorithm might lead to false classification. This problem is solved by applying the examining finger length ratio on average. This method has the disadvantage that two fingers may be classified into the same class of the finger. This problem has been overcome by choosing the most likely combinations of fingers. This system can recognize the 31 movement has been established with the recognition rate of 90.45%, and 1.5 seconds.

Akmeliawati [30] presented an automatic visual-based sign language translation system. Our proposed automatic sign-language translator provides a real-time English translation of the Malaysia SL. Sign language translator can recognise both fingerspelling and sign gestures that involve static and motion signs. It trained neural networks are used to identify the signs to translate into English.

IV. Conclusion

In this paper we have presented a review of sign language recognition with Neural Networks and HMM approaches. 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. Some researches that handle sign language recognition problem using different methods (Neural Networks and HMM) systems are discussed with detailed showing their advantages and disadvantages. Comparison was made between each of these methods, as seen different Neural Networks systems are used in different stages of recognition systems according to the problem nature, its complexity, and the environment available. 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. The Hidden Markov Model (HMM) classifier also proves interesting in sign recognition due its ability to model words based on sets of predefined states.

The major issues relate to the sign language translator system are accuracy and efficiency. Therefore, it is vital to use the right sign capturing method for integrating with the right sign language recognition methods. In addition, to produce a good sign language translator system, some researchers have used a combination sign language methods such as [21, 31].

To overcome the accuracy and efficiency problems in a sign language system, this study proposed the following solution: a sign language recognition method using hybrid Fuzzy and Neural Network with sign capturing based on Kinect camera.

TABLE I. COMPARING BETWEEN METODS

Authors	Year	Method	Advantages	Disadvantages
Kouichi [26] for Japanese Sign Language	1999	ANN (Data Glove)	The system is simple and can recognize a word.	Learning time of both network systems take a long time.
Jiong *et al.* [18] for Chinese Sign Language (CSL)	2000	HMM (CyberGloves,3D Tracker)	The approach for extracting signer position independent features is very powerful for sign language recognition system in practical applications.	It required the addition of bigram models, if not worse recognition performance.
Tani Bata *et al.* [20] for JSL recognition system	2002	HMM	System could recognize 65 JSL words in the experiment with real images in a complex background.	The system cannot recognize JSL sentences.
Volger [22] for American Sign Language .	2004	HMM	PaHMMs can improve the robustness of ASL recognition even on a small scale.	The system cannot recognize a larger vocabulary, hand configuration, orientation, and facial expressions.
Bowden *et al.* [21] for British Sign Language system (BSL)	2004	HMM	The Result rates as high as 97.67% for a lexicon of 43 words using only single instance training.	The system cannot recognize BSL sentences.
Akmeliawati [30] for Malaysian Sign Language system.	2007	ANN(Camera, Colored Glove)	The system achieved the recognition rate of over 90%.	The signs that are similar in posture and gesture to another sign can be misinterpreted, resulting in a decrease in accuracy of the system.
Gonzalo [28] for Real time gesture recognition	2007	ANN	The system is fast, simple, and modular. The recognition rate was achieved 94% from testing the dataset.	Person's movement and the noise was very influenced by the results. The system cannot be used to predict all movement
Manar [25] for Arabic Sign Language	2008	ANN(Colored glove, Digital Camera)	Help the network to stabilize network behavior, adding the ability to recognize hand gestures. It's using two test systems and networks with a lot of pictures.	The problems are: the feature extraction stage, the determination of the best areas of the colored areas is difficult, and the difficulty of determining the center of the hand for fingertip noise or image has been covered by a color.
Hninn [25]: for Myanmar Sign Language	2009	ANN(Digital Camera)	The system is easy to use, and do not need to use any special hardware. The system can use the MATLAB toolbox.	Training images are needed to test the performance of the system. Implementation of the MATLAB language is slower than the others but the fast execution time.
Stergiopoulou [29] Shape fittin technique	2009	ANN(Digital Camera)	This system can recognize with the recognition rate of 90.45%, and 1.5 seconds.	Two fingers may be classified into the same class of the finger.
Lang et al. (2011) for Sign Language Recognition Using Kinect	HMM	Recognition rate of > 97.00%	The experiment for eight out of nine signs	

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