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Sign Language Recognition Application Systems for Deaf-Mute People: A Review Based on Input-Process-Output

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Abstract

Sign Language Recognition is a breakthrough for helping deaf-mute people and has been researched for many years. Unfortunately, every research has its own limitations and are still unable to be used commercially. Some of the researches have known to be successful for recognizing sign language, but require an expensive cost to be commercialized. Nowadays, researchers have gotten more attention for developing Sign Language Recognition that can be used commercially. Researchers do their researches in various ways. It starts from the data acquisition methods. The data acquisition method varies because of the cost needed for a good device, but cheap method is needed for the Sign Language Recognition System to be commercialized. The methods used in developing Sign Language Recognition are also varied between researchers. Each method has its own strength compare to other methods and researchers are still using different methods in developing their own Sign Language Recognition. Each method also has its own limitations compared to other methods. The aim of this paper is to review the sign language recognition approaches and find the best method that has been used by researchers. Hence other researchers can get more information about the methods used and could develop better Sign Language Application Systems in the future.

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Keywords: sign language recognition; application of sign language; data input; deaf; mute;

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1. Introduction

Deaf is a disability that impair their hearing and make them unable to hear [1], while mute is a disability that impair their speaking and make them unable to speak [2]. Both are only disabled at their hearing and/or speaking, therefore can still do much other things. The only thing that separate them and the normal people is communication. If there is a way for normal people and deaf-mute people to communicate, the deaf-mute people can easily live like a normal person. And the only way for them to communicate is through sign language.

While sign language is very important to deaf-mute people, to communicate both with normal people and with themselves, is still getting little attention from the normal people. We as the normal people, tend to ignore the importance of sign language, unless there are loved ones who are deaf-mute. One of the solution to communicate with the deaf-mute people is by using the services of sign language interpreter. But the usage of sign language interpreter can be costly. Cheap solution is required so that the deaf-mute and normal people can communicate normally.

Therefore, researchers want to find a way for the deaf-mute people so that they can communicate easily with normal person. The breakthrough for this is the Sign Language Recognition System. The system aims to recognize the sign language, and translate it to the local language via text or speech. However, building this system cost very much and are difficult to be applied for daily use. Early researches have known to be successful in Sign Language Recognition System by using data gloves. But, the high cost of the gloves and wearable character make it difficult to be commercialized [3]. Knowing that, researchers then try to develop a pure vision Sign Language Recognition Systems. However, it is also coming with difficulties, especially to precisely track hands movements.

The problems of developing sign language recognition ranges from the image acquisition to the classification process. Researchers are still finding the best method for the image acquisition. Gathering images using camera gives the difficulties of image pre-processing. Meanwhile, using active sensor device can be costly. Classification methods also give researchers some drawbacks. Wide choice of recognition method makes researchers unable to focus on one best method. Choosing one method to be focused on, tends to make other method that may be better suit for Sign Language Recognition, not being tested. Trying out other methods makes researchers barely develops one method to its fullest potentials.

This paper aims to discuss the Sign Language Recognition System that are being used by researchers. In this paper, we will discuss about the Sign Language Recognition form application point of view. This paper will talk about the device used in getting the data, data acquisition, such as data from early researches or self-made data, the recognition method that are recently used by researchers, and the output of previous researches.

2. Data Acquisition

The main device used as input process in Sign Language Recognition (SLR) is camera. The SLR input data is in the form of gesture image that can be easily captured by camera. Some researchers still use simple camera to capture the image. Some researcher argue that they use camera and no gloves to prevent the difficulties when using sensory gloves [4]. Usually, cameras support many video format, so that we need to specify the default format and the format we want to use by using digitizer configuration format (DCF) file [5]. Some researchers also use higher specification camera because the web camera's image is blurred [6]. [7] used camera to capture 30 frames per second real-time video, which was then analyzed for dynamic gestures frame by frame. To extract the skin region, the system used skin filter and then for every frame to image is converted into HSV color space. [8] uses 4 cameras for the data acquisition, -20°, -10°, 10° and 20° position from the center respectively for each camera. In paper [9] also used a webcam through MATLAB for capturing the image and then stored in a directory. Signer must be ready to perform sign language hand gesture before clicking the start button in the application and click the Stop button when the signer is done performing the gesture.

There is also other device named Microsoft Kinect, which is used to capture images. Nowadays, Kinect is widely used by researchers because of its feature. Kinect can provide color video stream and depth video stream simultaneously. With depth data, background segmentation can be done easily. [10], [11], [12] and [3] uses Kinect for Sign Language Recognition. In paper [13] which also used Kinect extracted hand information from skeletal data from 20 joints they are X, and Y position of each joints, wrist, spine, shoulder and hip. (ini citation nya bukan nomor 9, gw gaktau refresh nya gmn). A sample of Kinect video stream is shown in Fig. 1.

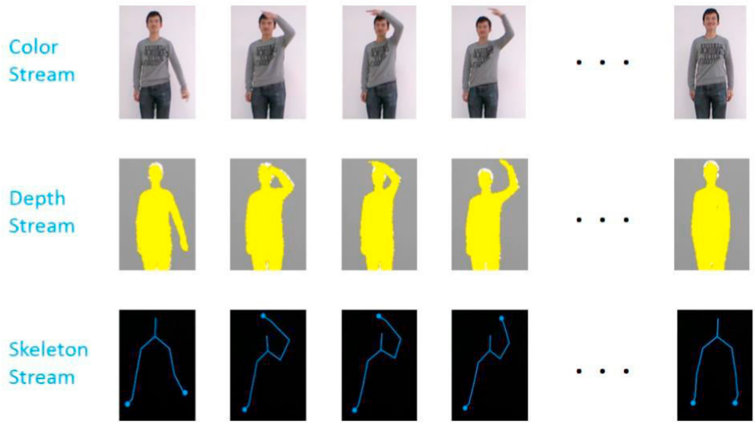

Fig. 1. Example of Kinect color and depth video stream

There are other methods to acquire input data, such as accelerometer and sensory gloves. [14] uses camera and color gloves to acquire the feature they need. The proposed system in [15] is using 3-axis accelerometer and flex sensors. The flex sensors are planted inside the gloves and provides fingers' flexes. The accelerometer provides tilting movement of palms. [16] uses two Cybergloves and three Pohelmus 3SPACE-Position Trackers. [17] uses 5-Dimensional Tracker to provide the input data. The dataset consists of 22-dimensional feature vectors: x, y, z, roll, pitch, yaw, thumb bend, forefinger bend, middle finger bend, ring finger bend, little finger bend, and other 11 features from right and left hands. [18] uses accelerometer (ACC) and surface electromyographic (sEMG). ACC can easily distinguish hand orientations and movements with different trajectories. While sEMG can measure the electric activity of muscles.

Another system used Leap Motion Controller (LMC) to acquire the data [19]. LMC is [20] a touchless controller developed by technology company based in San Francisco called Leap Motion. It can operate roughly around 200 frames rate per second and is able to detect and track hands, fingers, and finger-like objects.

Most of researchers acquire their training data by recording the data from their signer. [6] acquire their dataset from Indian Sign Language alphabets. They use their own dataset because there is no ISL dataset available. [4], [8] and [5] also acquire their own dataset from Indian Sign Language alphabets. [10] also use their own datasets because there is no available Kinect-based dataset of sign language. Their dataset contains of 25 daily used vocabulary. [3] collects 3 datasets from deaf students. Dataset 1 contains of 370 daily signs of Chinese Sign Language, while dataset 2 and 3 contains of 1000 vocabularies of Chinese Sign Language, signed by various number of signers. [14] uses their own recognition vocabulary that contains 223 two-handed and 216 one-handed signs. With 4 samples collected for training and 1 sample for training, total of 1756 training and 439 test samples are taken. [11] uses a database which contains of 239 Chinese Sign Language Words. [18] collect their data from Chinese Sign Language teacher and students, with the dataset contains 200 CSL common sentence constituted by 181 CSL words. [16] uses a large vocabulary, consist of 5113 signs from 6 signers, with a total of 61,356 samples. The words are taken from Chinese Sign Language dictionary with the synonym excluded. [7] used 4 signs gestures of Indian Sign Language, those gestures consist of 'A', 'B', 'C', and 'Hello'. [19]'s system used 10 samples of 28 Arabic Alphabet signs, entirely the system analyzed and processed 2800 frames of data. While many researchers make their own datasets, [17] uses datasets from American Sign Language Image Dataset (ASLID) which is taken from Gallaudet Dictionary videos. [21] uses datasets from ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) – 2010 and is intended to be used for the challenge. [12] also uses outsource datasets called ChaLearn Looking at People 2014 (CLAP14). [22] uses 3 dataset to compare each other with the proposed method, they are: RWTH-Phoenix-Weather 12, RWTH-Phoenix-Weather Multisigner 2014, SIGNUM single signer. Table 1 summarizes data acquisition method used by various researchers.

Table 1. Data Acquisition Method from Researchers

Authors	Method
[14], [4], [5], [7], [9]	Web Camera
[6]	High Specification Camera
[14]	Camera and Color Gloves
[8]	4 Cameras
[3], [10], [11], [13]	Kinect
[15]	3-axis accelerometer and flex sensors
[17]	5-dimensional tracker
[16]	Two Cybergloves and 3SPACE-position tracker
[21]	Accelerometer and surface electromyography
[19]	Leap Motion Controller

3. Processing Methods

One of the processing method widely used in SLR is the Hidden Markov Model (HMM). [18] uses the HMM algorithm by combining it with another algorithm. Firstly, they use fuzzy K-means algorithm to do the Hand Shape Classifier. The hand shapes are classified to 8 clusters for the right hand and 7 clusters for the left hand (based on the algorithm testing). And then, the orientation classifier is done by classifying the direction which the palm is facing. Due to large variety of SLR gesture, the classification is done by classifying the onset and offset of hand orientation, as it is relatively consistent when same sign is done repeatedly. Lastly, they do the movement classifier by using HMM. The HMM they use is Multi Stream HMM (MSHMM). It is based on two standard single-stream HMM. The ACC and sEMG data feature sets are used to train the stream via Baum-Welch algorithm. The other method of HMM is used by [3] which is called Light-HMM. They select the key frames through low-rank approximation and adaptively determine the hidden states in HMM. By using such method, the key frames can be reduced and the estimation of hidden states can be more precise. The basic idea is that the frames with linearly independent features will be selected as key frames and the others will be discarded. There are also a HMM approach that is called TD-HMM [14]. This method uses the method similar to continuous HMM (CHMM), with the amount of computation is reduced by tying similar Gaussian mixture components.

The other processing method is neural network. [10] uses neural network called 3D Convolutional Neural Network (CNN). The 3D CNN method is based on 2D CNN which is used in speech and image recognition. The 2D CNN implementation is done by extracting a layer to feature map by using kernel window called local receptive field. It reduces the free variables and increase generalization capability of the network. The 3D CNN is implemented using 2D CNN by adding the motion feature. The 3D Convolution is achieved by convolving 3D kernel with the cube formed by stacking multiple neighboring frames together. [12] uses two 3D-CNN in their research, for extracting hand and upper body features. Each CNN is 3 layers deep. They also applied local contrast normalization (LCN) for the first two layer and the neurons are rectified linear units (ReLU). [21] uses 2D Convolutional Neural Network in their research, with unusual feature in their network architecture. The unusual features are ReLU Nonlinearity, multiple GPUs, Local Response Normalization, and Overlapping Pooling. The ReLU Nonlinearity is the alternative of traditional neuron models in CNN. It trains several times faster than traditional CNN and is best fit to be used in a big dataset. They also use multiple GPUs to train their data because of the size of data that do not fit in one GPU. While ReLU on its own does not need normalization, they still add the Local Response Normalization to their network. The normalization aids in generalization and it decreases the test error rates. They also use the overlapping method, differ from traditional CNN that does not overlap, and find it more difficult to cause overfitting. They also use Data Augmentation and Dropout method that reduces overfitting. The dropout method is a new method that drops neurons so that the network is forced to learn more robust feature.

There are also researches that use simple ANN for the recognition method. [8] uses ANN combined with Elliptical Fourier Descriptor (EFD). The EFD acts as the feature extractor that describe image in a 2D curve. The feature obtained by using EFD is unique from one sign and the other. The feature then recognized by using ANN.

[19] compares two methods that are used for the recognition, the Naïve Bayes Classifier (NBC) and Multilayer Perceptron (MLP). The NBC approach is based on counting the trade-offs from many classification decisions using probability. One common rule used by NBC is the Maximum A Posterior Probability (MAP). While the MLP (well known as ANN) is a neural network that learns from examples by constructing input and output mapping. They used backpropagation algorithm and Least-Mean-Square algorithm to minimize the difference of mean square between real network and desired network.

The other, unsupervised neural network method used in SLR is Self-Organizing Map (SOM). [6] used the SOM to automatically cluster the feature data. They used a kind of SOM called the Kohonen Network. The Kohonen Network has a feed forward structure with a single computational layer arranged in rows and columns. The Kohonen SOM recognize images based on minimum Euclidean distance for similarity measurement.

[16] on the other hand, combine 3 methods in their research. They use Self Organizing Feature Map (SOFM), Simple Recurrent Network (SRN) and Hidden Markov Model (HMM). THE SOFM are used for the feature extraction. The result of the SOFM are inputted to the SRM to be segmented. The segmentation results are inputted to the HMM framework and are recognized by using the lattice Viterbi algorithm. Another combination of HMM algorithm found in [13] which used SVM algorithm to train and recognize hand shapes. The training stage performed by representing the percentage of hand pixel and the average depth information of both hands in confusion matrix. The hand directions are divided into 6 classes for single-handed and another 6 classes for two-handed. Then HMM algorithm is applied to recognize the direction of the gestures.

There is other method involving Support Vector Machine (SVM). [17] named it SimpSVM, stands for Simple Support Vector Machine. The main goal of SimpSVM is to approximate the normal vector and reduce the set expansion. The goal of the reduced set methods is to choose the smallest number and corresponding reduced set, so that the resulting loss is still acceptable. [7] used SVM to classify the feature vector of the extracted features, the features are including Hi-moments which are location, angle, and shape invariant moments, fingertips, and trajectory tracking. To acquire fingertips features the system used spatial domain method.

Other researches use self-designed methods. [5] uses the wavelet family method. The method is used to detect the peaks of signals. Wavelet analysis is a decomposition method that produces a family of hierarchically organized decompositions. The selection of the decompositions will depend on signal and experience and is usually chosen based on desired low-pass cutoff frequency. The signals then are recognize based on finger tips. The signals of gesture are then matched with gesture database. The template matching uses the prediction table. Fuzzy Rule set can be used to make the classification after the finger tips has been detected.

The other self-designed method is proposed by [4], which is named Eigen Value Weighted Euclidean Distance. The method involves two levels of classification. The first one is Euclidean Distance Classification. The Euclidean distance is found between two of the Eigenvectors from the test image and the database image. They specified five Eigenvectors, so that there are five Euclidean distances. From the Euclidean distances, they find the minimum value of each. Then the values are classified based on the second classification, named Eigenvalue weighted Euclidean distance. The difference of eigenvalue from the images is calculated. Then the value is added by the Euclidean distance found in the first classification. The classification is based on the minimum value of the second classification. Table 2 summarizes classification method proposed by various researchers.

Paper [23] proposed sign language recognition by using SIFT algorithm to compare the extracted features with images stored in the database. Another similar work is found in [24]. SIFT algorithm is an interesting method because it is robust against rotation, translation or scaling variation and it produces "large collection of local feature vectors". SIFT algorithm needs 4 stages of filtering approach to extract the features [25]. First is Difference of Gaussian
The first method used to construct the Gaussian function is by filtering (convolution). Second is Extrema Detection. This step is to find the extrema point from DOG. Each pixel in the image compared with its 26 neighbors. The compared value can be minimum or maximum, this is the extrema. Third is the Key Points Elimination. This step is to eliminate the low contrast or a poorly localized on an edge. The last is Orientation Assignment aim to assign consistent orientation by calculating the gradient (m) and the orientation (θ) to the keypoints.

Table 2. Classification Method from Researchers

Authors	Method
[3], [14], [18]	HMM
[10], [21], [12]	Convolutional Neural Network
[16]	SOFM, SRN, HMM
[13]	SVM and HMM
[6]	Kohonen Self Organizing Map
[17], [7]	Simple Support Vector Machine
[5]	Wavelet Family Method
[4]	Accelerometer and surface electromyography
[19]	Multilayer Perceptron
[19]	Naïve Bayes Classifier

4. Application Result

From the HMM method, there are three kinds of implementations: light HMM, multi stream HMM and tied-density HMM. [3] with the Light-HMM method has an accuracy of 83,6%. While [18] achieved 99.4% for training dataset and 98,9% for testing dataset recognition rate of overall sub-word segment detection, 99% for training dataset and 96,5% for testing dataset recognition rate of overall sub-word detection, and 96,9% for training dataset and 86,7% for testing dataset recognition rate of overall sentence detection. [14] using the TDHMM acquire an accuracy of 91,3%. [13] by using the SVM and HMM algorithm achieved 85.14% for demonstrating a Taiwanese sign language recognition.

[10] with 3D-CNN has an accuracy of 94,2%, while [12] has the accuracy of 78,8% and [21] has an accuracy of 83% in a contest dataset. [16] with the SOFM, SRN, and HMM combined method has achieved an accuracy of 91,3%. While [6] with the Kohonen SOM has 80% accuracy. 98,09% accuracy is achieved by using SimpSVM method [17], and 97,5% accuracy is achieved by using SVM [7]. 97% accuracy is achieved by using Eigen value weighted Euclidean distance method [4]. Meanwhile, 95,1% accuracy is achieved by [8] and 100% accuracy is achieved by [5] in simple recognition. Table 3 shows the comparison result of Sign Language Recognition system proposed by researchers.

Table 3. Comparison result of Sign Language Recognition

Authors	Method or Application Systems	Accuracy Result
[3]	Light-HMM	83,6%
[18]	Multi Stream HMM	86,7%
[10]	3D-CNN	94,2%
[12]	3D-CNN	78,8%
[8]	EFD and ANN	91,5%
[21]	Convolutional Neural Network	83%
[6]	Kohonen SOM	80%
[17]	SimpSVM	98,9%
[4]	Eigen Value	97%
[5]	Wavelet Family	100%
[14]	Tied-Density HMM	91,3%
[16]	SOFM, SRN, HMM	91,3%
[13]	SVM and HMM	85,14%
[7]	SVM	97,5%

5. Analysis and Discussions

Sign Language Recognition Application Systems is developed in two steps, data acquisition and classification. There are two data acquisition methods that are often used by researchers, camera and Microsoft Kinect. [4], [5], and [6] uses camera for their Sign Language Recognition Systems. The main advantage from using camera is that it removes the needs of sensors in sensory gloves and reduce cost from building the system. As we know that camera is quite cheap and is available in almost all laptops. [6] are using high specification camera because of the blur caused by web camera. But even though it is high specification camera, it is still available in most of smartphones. [8] even use 4 cameras to acquire the data they need. The disadvantage of using web camera, or simply camera, is that good image pre-processing of obtaining the feature is needed. The Microsoft Kinect is the other popular method used by researchers to acquire their data. Microsoft Kinect is getting more popular among researchers as it provides more data and it is needed by researchers. [10], [11], [12], [13] and [3] uses Kinect to acquire their data. the advantages of using Kinect is that it provides the depth data of the video stream. The depth data is very useful as it can easily distinguish the background and the signer. Furthermore, it can be used to distinguish hands and body as the signer usually perform sign language by hands in front of their body. The disadvantage is that the Microsoft Kinect device is costly and it should be connected to computer. [14] uses simple camera and color gloves to differentiate both hands and ease the feature extraction process. [15] are using 3-axis accelerometer and flex sensors; [17] uses 5-Dimensional Tracker; while [18] uses accelerometer (ACC) and surface electromyography (sEMG). [16] uses 2 Cybergloves and 3SPACE-position tracker. All of these gloves are equipped with sensors attached to the gloves. The advantage is that it provides all the data needed more accurately as it also provides fingers movement data. The disadvantages are that they are costly and are difficult to be used commercially.

Classification methods are also varying from researchers. Researchers tend to develop their own concept, based on known methods, to give better result in recognizing the sign language. As for classification methods, the most ancient, popular method is HMM. Researchers has been using HMM for developing Sign Language Recognition for years. [18], [14] and [3] is using modified HMM for their researches. The other method that is gaining more popularity in Sign Language Recognition researches is neural network. Neural network is known to be successful in developing speech recognition, and is now being used in Sign Language Recognition. [10] and [12] uses 3D Convolutional Neural Network to recognize the sign language. [21] also uses Convolutional Neural Network in their research that is used in a competition and achieved great results. SOM is also used in Sign Language Recognition as its ability to perform self-clustering. [6] is using the SOM method for classifying the sign languages. [17] is using a modified SVM called SimpSVM to recognize sign languages. While most of the method are done separately, [16] in their research, uses combination method of SOFM, SRM and HMM. The combination method beats HMM in their own researches. There are other researches that uses self-designed methods. One of them is using the wavelet family method [5]; and there are also researchers that are using Eigen Value and Euclidean Distance to classify the sign language [4]. The HMM method is still the most popular method used by researchers, but other methods seems to be getting more popular and tend to be researched.

While HMM is still the most popular method, the most accurate from the papers is still on 86,7 %, while the 3D-CNN method has gained 94,2 % accuracy. The combination method of SOFM, SRM and HMM is able to achieve 91,3% accuracy. [8] using simple ANN is able to achieve 95,1% accuracy. Using the Eigenvalue and Euclidean Distance, [4] can get 97% accuracy. The SVM method is able to achieve 97,5% [7]. While the SimpSVM method can recognize up to 98,9% accuracy. The wavelet family method can achieve 100% accuracy but only tested for simple hand sign. The accuracy comparison cannot be easily done because of the various approaches and non-standardized evaluation protocol. Every research has its own limitations and differences. Some method may be better fit on the condition stated by a researcher, but the other method can be more accurate on other research. The best method may be vary depending on what language is being developed and what limitation is stated by the researcher.

6. Conclusion and future works

Sign Language Recognition System has been developed from classifying only static signs and alphabets, to the system that can successfully recognize dynamic movements that comes in continuous sequences of images. Researcher nowadays are paying more attention to make a large vocabulary for sign language recognition systems. Many researchers are developing their Sign Language Recognition System by using small vocabulary and self-made database. Large database build for Sign Language Recognition System is still not available for some of the country that involved in developing Sign Language Recognition System. Especially the Kinect-based data, which provide the color stream and depth stream video. The classification method of identifying the sign language is also varied from researchers. Using their own ideas and limitations for the Sign Language Recognition System, the comparison of one method to another method is still subjective. Fair and direct comparison between approaches are limited because of the variation of sign language in different countries and the difference in limitation set by each researcher. Variation of sign language in most of the country is based on their grammar and their way to present each word, such as presenting the language by word or by sentence.

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