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## Characterization of 3D Gestural Data on Sign Language by Extraction of Joint Kinematics



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### ABSTRACT

Sign language recognition system is complex and particularly hard to recognize the sign and gesture from those people who have aphasia and apraxia; for example, joint contracture. Therefore, the simplified version of gesture is useful for them to communicate better and for recognition purpose. The feature subset selection has been a focus in research commonly applied in many multimedia and medical applications such as gestural recognition, physiological signal analysis, etc. The characteristics of these data are usually high dimensional as they consist of a series of observations from many variables at a time. In this research, a computational process is proposed to reduce the feature set as originally adopted from a hand gesture capture system. The subset selection is first based on biomechanical characteristics. The objective is to provide a faster, more cost-effective process for the flexibility of capture and recognition based on the selected target group. At the same time, it enhances the knowledge and better understanding of the underlying process that generates the gestural data.

## **INTRODUCTION**

Nowadays, there are more and more different applications employing hand gesture recognition techniques. The hand gesture has provided significant methods of communication in human daily interaction and has been extensively explored in the human-computer interaction (HCI) studies [1]. Gestures include the movement of the fingers, hands or other parts of the body. They are culture specific and can convey many different meanings even in different societies or cultural places. For example, American Sign Language (ASL) fingerspelling recognition system was designed and constructed in order to translate the ASL alphabet into the corresponding printed and spoken English letters [2]. The structure of sign language is represented as a combination of basic components of gestures and the sign language can then be recognized by using those components [3].

### **Sign Language for Special Needs**

For those people who suffer from aphasia and apraxia, sign language is one of the ways for them to communicate with others. Aphasia is an impairment of language, affecting the production or comprehension of speech and the ability to read or write. It is always due to injury to the brain, particularly in older individuals. Apraxia is neurological condition characterized by loss of the ability to perform activities that a person is physically able and willing to do. It is caused by brain damage related to conditions such as head injury, stroke, brain tumor, and Alzheimer's disease. That damage can affect the brain's ability to correctly signal instructions to the body. Those patients who suffer from aphasia and apraxia would find it difficult to say some words [4] or to make hand and finger gestures. The hand gesture recognition system may not read their vague pose and hand gesture. Therefore, feature subset selection based on formal sign language is one of the research approaches to seek for solution in between. On one hand, these people can still communicate based on formal set of sign language defined. On the other hand, the hand gesture can be simplified for performance and robust for recognition system.

### **Recognition Systems**

More and more hand gesture recognition system makes use of three dimensional technology and coordinate system to capture hand shape and calculate the range of motion for each finger. There

are two popular types of approaches, appearance-based solutions and device-based solutions to model the hand gesture for interpretation. However, most related works are about the hand gesture recognition for general users. There is only little consideration in terms of flexibility in coordination of various joints of a hand through different key positions and target for aphasia and apraxic users. Therefore, simplifying strategies can be based on temporal pattern of movements [5]. The aim of this study is to apply the method, which allows people who suffer from aphasia and apraxia could use computers to recognize their gesture easily.

## **MATERIALS AND METHODS**

### **Joint Kinematics**

The concept of joint kinematics from the biomechanical literature is used to abstract the movement. Fingers segments are linked to each other at the joints. The joint structure determines the types of joint motions allowed at the joint. In human movement, it is the study of the positions, angles, velocities, and accelerations of body segments and joints during motion.

### **Range of Motion**



Range of motion (ROM) is a quantity that defines the joint movement by measuring the angle from the starting position of an axis to its position at the end of its full range of the movement. It is possible to calculate the range of motion per joint by using the sensor values acquired by sensory device attached to a human hand [6]. With the knowledge on the hand posture of all the hand signs concerned, the overall range of motion needed per finger joint can be defined.

## **RESULTS AND DISCUSSION**

By accumulating all these 1s, each pair of sign can then be compared and revealing the number of bits that can be distinguished between each other. The process resulted in a matrix of 24 x 24, which are the number of alphabets. If the value is 0, that means the two signs cannot be distinguished from each other. Higher the value, higher the probability that the sign can be distinguished. A threshold T, between 1 and 8, was set as the minimum number of features that has to be different between two signs. If the number of features between two signs meets or above this threshold, the two signs are said to fulfil the criteria for recognition. The number of

sign pairs that fulfil the criteria with respect to one alphabet can be expressed as a percentage as the whole sign language set. These percentages are illustrated in Table 1.

**Table 1. Percentages of sign pairs that fulfil the threshold criteria for feature set  $S_t''$ .**

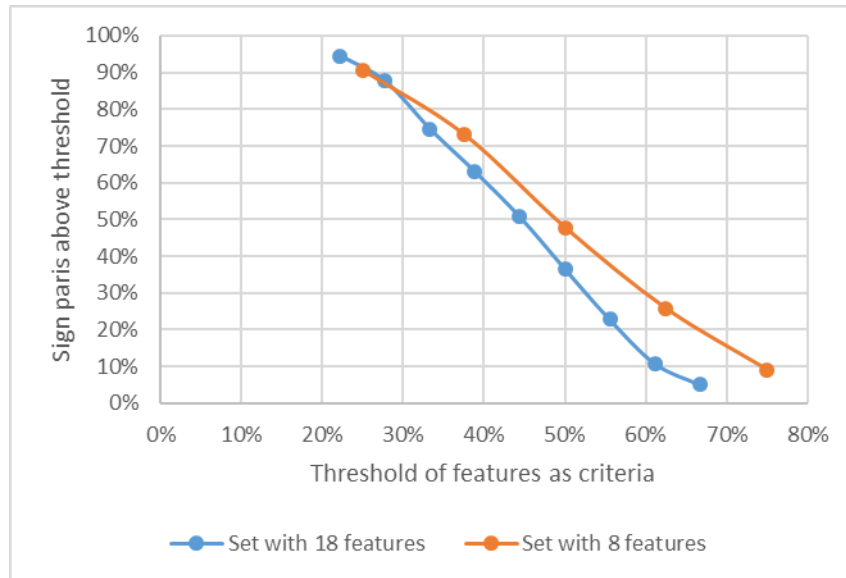
<b>Threshold (T)</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>
<b>A</b>	96%	78%	70%	43%	26%
<b>B</b>	96%	83%	61%	39%	13%
<b>C</b>	100%	91%	61%	26%	13%
<b>D</b>	91%	74%	26%	4%	0%
<b>E</b>	100%	87%	70%	48%	26%
<b>F</b>	96%	83%	65%	52%	13%
<b>G</b>	87%	61%	39%	13%	0%
<b>H</b>	83%	65%	39%	17%	0%
<b>I</b>	96%	87%	65%	35%	17%
<b>K</b>	100%	100%	70%	30%	17%
<b>L</b>	87%	61%	39%	13%	0%
<b>M</b>	96%	83%	65%	52%	13%
<b>N</b>	100%	78%	26%	9%	0%
<b>O</b>	96%	74%	39%	22%	0%
<b>P</b>	83%	61%	39%	22%	9%
<b>Q</b>	83%	52%	35%	17%	4%
<b>R</b>	83%	52%	35%	17%	4%
<b>S</b>	100%	78%	48%	22%	9%
<b>T</b>	87%	78%	48%	30%	13%
<b>U</b>	83%	61%	39%	22%	9%
<b>V</b>	83%	61%	39%	22%	9%
<b>W</b>	91%	78%	57%	26%	13%
<b>X</b>	70%	52%	35%	22%	9%
<b>Y</b>	91%	78%	39%	13%	0%
<b>Mean</b>	91%	73%	48%	26%	9%

There are signs of alphabet that can relatively easy to get distinguished from others. They have percentages of higher values at the same threshold value. Using the same computational process, results can be calculated for the feature set of  $S_t'$  as illustrated in Table 2.

**Table 2. Percentages of sign pairs that fulfil the threshold criteria for feature set  $S_t'$ .**

<b>Threshold (T)</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>	<b>8</b>	<b>9</b>	<b>10</b>	<b>11</b>	<b>12</b>
<b>A</b>	96%	91%	83%	74%	57%	52%	48%	30%	26%
<b>B</b>	91%	87%	78%	70%	61%	43%	30%	22%	9%
<b>C</b>	100%	100%	100%	96%	74%	48%	26%	9%	9%
<b>D</b>	91%	87%	65%	43%	26%	17%	9%	0%	0%
<b>E</b>	100%	100%	91%	83%	78%	57%	43%	22%	4%
<b>F</b>	96%	91%	87%	70%	61%	57%	39%	22%	13%
<b>G</b>	91%	78%	65%	61%	35%	13%	9%	0%	0%
<b>H</b>	91%	83%	78%	61%	48%	43%	13%	4%	4%
<b>I</b>	100%	96%	87%	74%	52%	30%	17%	9%	4%
<b>K</b>	100%	96%	87%	70%	39%	26%	13%	4%	0%
<b>L</b>	96%	91%	65%	57%	48%	30%	22%	9%	4%
<b>M</b>	96%	87%	78%	74%	70%	43%	30%	22%	9%
<b>N</b>	96%	87%	65%	43%	35%	17%	13%	9%	0%
<b>O</b>	96%	91%	74%	74%	61%	43%	22%	0%	0%
<b>P</b>	87%	70%	52%	43%	39%	30%	9%	4%	0%
<b>Q</b>	87%	70%	52%	39%	26%	13%	9%	0%	0%
<b>R</b>	96%	87%	70%	52%	39%	26%	13%	9%	0%
<b>S</b>	100%	96%	83%	78%	74%	61%	39%	17%	9%
<b>T</b>	96%	87%	78%	70%	57%	43%	26%	13%	9%
<b>U</b>	87%	70%	48%	39%	39%	26%	13%	0%	0%
<b>V</b>	91%	91%	78%	57%	43%	35%	22%	13%	0%
<b>W</b>	91%	87%	83%	70%	57%	48%	35%	17%	17%
<b>X</b>	96%	87%	65%	48%	43%	30%	13%	9%	0%
<b>Y</b>	100%	96%	78%	70%	57%	43%	35%	17%	4%
<b>Mean</b>	95%	88%	75%	63%	51%	37%	23%	11%	5%

To compare the performance of these two table of results, the T is normalized based on the maximum number of features in the given set. The graph that compares the results based on the two feature sets is illustrated in Figure 1.



**Figure 1. Comparison between feature sets.**

Based on the same percentage of features used, it can be seen that higher percentage of sign pairs meeting the criteria for the set  $S_t''$  compared to  $S_t'$ . It can be illustrated by drawing vertical lines inside Figure 1 starting from 30%. For every line on the right hand side of 30%, the percentage as resulted from feature 8 is larger than those of 18 features. This means the features within the  $S_t''$  is more effective for recognition than those of  $S_t'$ . The results reach our initial object to provide a feature subset for faster and more cost-effective process for the capture and recognition. Since the process includes a discretization process that defines a threshold value flavour for particular needs, the process is customized for people who suffer from aphasia and apraxia in particular.

## CONCLUSION

In this research, an approach is proposed for feature subset selection preparing for hand gestures recognition. The process is first based on joint kinematics to eliminate those features that do not have a considerable amount of magnitude of movement in order to distinguish between the hand gestures of various alphabets in the set of sign language. This parameter was set based on the criteria for people with special needs, aphasia and apraxia in particular. The discretized values are then compared using bitwise comparison among the whole alphabet set of signs. This research can be further enhanced by capturing various subject groups with symptoms of aphasia

and apraxia. The computational process and evaluation method can then be validated with stronger evidence.

## REFERENCES

1. Howe LW, Wong F, Chekima, A. Comparison of hand segmentation methodologies for hand gesture recognition. International Symposium on Information Technology. 2008.
2. Jerome M, Pierre K, Richard F. American sign language fingerspelling recognition system. IEEE 29th Bioengineering Conference. 2003.
3. Hirohiko S, Masaru T, Masaru O. Description and recognition methods for sign language based on gesture components. 2<sup>nd</sup> International Conference on Intelligent User Interfaces. 1997.
4. Apraxia. 8/20/2017. Available from <http://medical-dictionary.thefreedictionary.com/apraxis>
5. Daniel BD, Renata CB, Madeo TR, Helton HB, Sarajane MP. Hand movement recognition for Brazilian Sign Language: A study using distance-based neural networks. Paper presented at the International Joint Conference on Neural Networks. 2009.
6. Reese NB. Joint Range of Motion and Muscle Length Testing. Saunders Publication; 2001.

