Recognition of Air-Drawn Alphanumeric Characters by Applying Slope Orientation Sequence Matching Algorithm Using Leap Motion Controller

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Abstract— **The study focused on the recognition of letters and numbers written in free air. The information of motion trajectory is captured by a leap motion and plot as continuous stream of points. From the major points, lines will be integrated and major slopes are defined. As an application of geometry, major slopes are transformed into directions. This is also called as slope orientation. The compilation of the slope orientation referred as Slope Orientation Sequence is used to uniquely represent Alphanumeric Characters. The characters will then be recognized by the system once the generated slope orientation sequence matched with the reference slope orientation sequence in the system program. The process of sets and subsets is applied in the matching process of the algorithm. In this paper, the researchers proposed a new method that can classify Alphanumeric Characters written in air. The experiment result demonstrates the reliability of the proposed method.**

Keywords—Alphanumeric Characters, Slope Orientation, Leap Motion Sensor, Air-drawn

I. Introduction

This Air-writing refers to an input mechanism that allows the user to write or draw in free space with hands or fingers. Similar to motion gesture, air-writing is tracked in continuous stream of data that contains a sequence of hand and finger movements. Air-writing is different from the conventional writing, since the latter uses the paper-pen-based writing and the former uses an imaginary board in the air for writing. Unlike handwritten characters, those drawn in 3D space has no pen-up and pen-down information that makes multi-stroke letters a unistroke. An Air drawn letter recognition is not a simple swipe or circular hand gesture that may represent discrete symbols, according to study, drawn letters is as good as speech. In this context, writing in air can be used as a communication mode particularly when communicating with a person at several distances.

Many researchers have conducted a study to accurately identify free-air movements in 3-Dimensional space using different kinds of sensors. Such works include's Yanmei and Chen's et.al "A Real-time Dynamic Hand Gesture Recognition System Using Kinect Sensor". This is a real-time Kinect-based dynamic HGR system which contains hand tracking, data processing, model training and gesture classification. Classical approach of Hidden Markov Model (HMM) and Support Vector Machine (SVM) are used as recognition algorithms. For the gestures 6, C, O, and V, less than 50% recognition rate were attained making an over-all average rate down to 82.86% of HMM. On the other hand, SVM classified most of the gestures as 100% but 60% on gesture O causing 95.42% of the over-all average rate.

In the study of Tsuchida et al entitled, "Handwritten Character recognition in the Air by Using Leap Motion Controller" it recognizes 46 Japanese Hiragana characters and 26 alphabet that got 84.54% accuracy for recognizing the English alphabet with an overall recognition rate of 86.7%. Moreover, in 2015, another study on "Numeral Gesture Recognition using Leap Motion Sensor" by Jayash Kumar Sharma et al., applied Geometric Template Matching method and used Leap Motion Sensor to capture free air numeral gestures ranging from 0-9. Gesture spotting, Features Identification, Recording of Gestures, Training and Classification were the three steps done in the system. However, the algorithm's weakness consists of the gestures containing open curve that resulted to failure in recognition. Therefore, the system was only able to achieve 70.2% classification rate. Letters containing curves, specifically open curves were the major problem of the previous studies. Other existing studies have problems on the size and shape of the letter. Due to misclassified letters, the accuracy rate of the system tends to decrease.

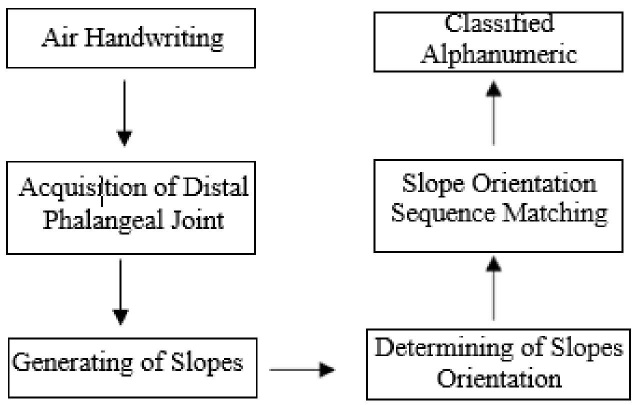

Fig. 1 The air writing recognition system

Due to problem in the previous studies, the researchers propose a recognition system using Slope Orientation Sequence Matching Algorithm. The system block diagram in Figure 1 shows the entire operation of the system. It consists of the air hand-writing as the system input, acquisition of human hand distal phalangeal joint coordinates, generating of slopes and angle formed, determining slope orientation,

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slope orientation matching, and the classified alphanumeric characters as the output of the system.

Air-Writing Recognition Technology is one of the most emerging technology in the field of human-machine interaction. In line with this, the study will be a great help in the academic and medical field in the society. The proposed algorithm is also a new concept in dynamic hand gesture recognition that can be used in the future studies.

II. METHODOLOGY

A. *Feature Extraction*

1. *Acquisition of Distal Phalangeal Joint*

The Leap Motion Sensor contains skeletal tracking feature that focuses on human's fingers within the interaction area of the device. Hence, the skeletal joint coordinates of the finger will be obtained. For this reason, Leap Motion Controller sensor is used in acquiring the distal phalangeal joint coordinates of the human hand.

As the user inputs an alphanumeric character in free-air, the system will continuously plot points and acquire its coordinates until the motion ends. Using Visual Studio 2012, as the program software and C# code, the system will integrate the acquired coordinates from the Leap Motion controller to the system program.

2. *Acquiring of Major Points*

Every stroke is composed of stream of points, from these points the system program then chooses major points that will represent the specific stroke. Major points are obtained based on the abrupt change between slope *n*. The researchers conducted three trials to determine the appropriate tolerance for slope *n* in acquiring the major points to be considered in analyzation. Note that tolerance is the smallest accepted value of change between slopes *n*.

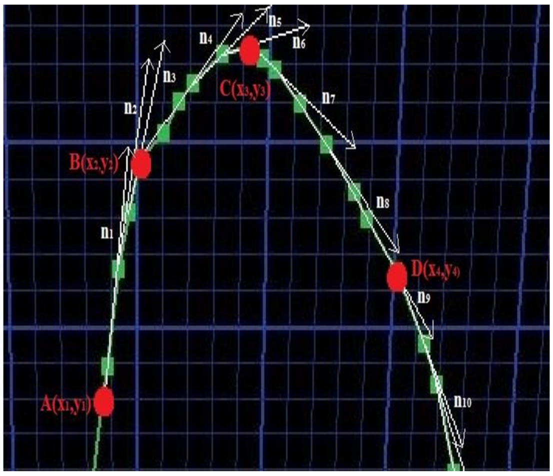


Fig. 2 Acquired major points from the gesture

Figure 2 displays the major points generated from the set tolerance *t*. This means that from the trials conducted, slopes *n* must have a difference of greater than or equal to, tolerance *t* .55 to be considered that an abrupt change is present. Hence, a major point is established as described in Table 1.

Table 1: Acquisition of Major Points base on tolerance *t*

Slopes *n*	Magnitude(k_n)	$\lvert kn-kn+1 \rvert$	$\lvert k_n-k_{n+1} \rvert -t$
1	3.2981	0	-0.55
2	3.0762	0.2219	-0.3281
3	2.8239	0.4742	-0.0758
4	2.6988	0.5993	**0.0493**

Slope n_1 will be considered as the first slope contained in the stroke that holds the first major point. In this context, slope n_1 will be the reference for defining if the succeeding slopes *n* are within the set tolerance *t*. As seen in Table 1, the change in value of slope n_2 and slope n_3 with respect to n_1 is less than the set tolerance *t*. However, the change between slope n_1 and slope n_4 surpass the tolerance *t*. As a result, a major point is established.

3. *Acquiring of Major Slopes*

The acquired two consecutive major points, composed of x and y coordinates, are then fed to the slope formula. The slope of a line is dependent in the value of change in x-coordinates Δx and change in y-coordinates Δy. Change in x-coordinate is defined as the horizontal length of the line produced by the two consecutive major points, while change in y-coordinates is responsible for vertical length.

4. *Defining Slope Orientation*

The acquired slope composed of change in x and y will determine the slope orientation which is divided into 8 categories namely: Up (U), Right (R), Down (D), Left (L), Right-Up (RU), Right-Down (RD), Left-Down (LD) and Left-Up (LU). When using leap motion sensor, there is a difficulty to input straight lines. Consequently, the researchers analyzed the average range of angles conducted by five (5) users with five (5) trials each when drawing straight lines - up, right, down and left.

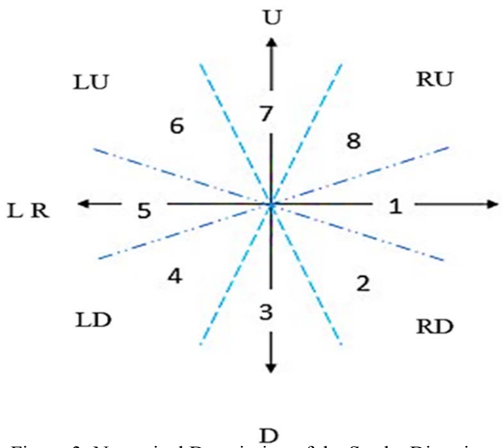


Figure 3: Numerical Description of the Stroke Direction

Figure 3 shows eight possible stroke directions and its corresponding numerical representation. These eight possible strokes will be the basis for identifying the orientation of the major slope.

Table 2: Stroke, Slope and Numerical Representation

STROKE	ΔX	ΔY	m	NUMERICAL VALUE
RIGHT	+	0	$-0.26795 < m < 0.26795$	1
RIGHT	+	-	$-0.26795 > m > -3.37205$	2
RIGHT	+	+	$0.26795 < m < 3.73205$	8
UP	0	+	$3.73205 < m < -3.73205$	7
DOWN	0	-	$3.73205 < m < -3.73205$	3
LEFT	-	-	$0.26795 < m < 3.73205$	4
LEFT	-	+	$-0.26795 > m > -3.73205$	6
LEFT	-	0	$-0.26795 < m < 0.26795$	5

Table 2 displays the relationship between strokes, slopes and the numerical representation. It also indicates how slopes are converted into slope orientation.

5. Determining Slope Orientation Sequence

Upon conducting 25 trials per alphanumeric character done by five users, the system program will record the number of slopes and the direction of each established slope.

B. Slope Orientation Sequence Matching

The process of recognition can be done by applying the concept of sets and subsets in mathematics. The user input gesture is integrated to form set G. The generated input set G is compared to the distinct reference set R.

Let A be the difference of the reference set R and generated set G.

$$S_i = \text{set of input slope sequence} = \{m_1 m_2 m_3 \ldots m_n\}$$

$$G = \{S_i\}$$

$$R = \{S1, S2, S3, S4 \ldots,\}$$

$$A = G/R = \text{set } G - \text{set } R$$

$$A = \{S_i - (S_1, S_2, S_3, S_4 \ldots S_t)\} \quad (1)$$

If the difference between set G and set R is equal to an empty set, A = **Ø**, therefore, the generated set G is a subset of reference set R. It also satisfies that the input slope sequence for a specific character is included in the templates of the specific alphanumeric character. Thus, recognition of the air drawn alphanumeric character occurs.

C. Determining the Reliability of the System

The reliability of the system to recognize the input gestures drawn in free air at the range of the Leap Motion Sensor was obtained by considering 1800 gesture sample (50 sample gesture per alphabet and numeral). The gesture recognition is done by five different users. Each respondents will perform a total of ten (10) trial observation for every alphanumeric character. The number of the gesture samples was based on the previous study for an ideal comparison. The previous study consists of 500 sample gestures.

The total number of successful recognitions are tallied along with the number of trials performed. The percentage of reliability of the recognition per alphanumeric character using the Slope Orientation Matching was computed by the formula below. Since the test will determine the number of successful recognition, it will also show how reliable the system to recognizing every character drawn in free air.

During the actual testing of the system*, the following are the conditions to be considered in order to determine whether the trial is a success*: (1) the generated input sequence for a particular character must match the reference slope sequence for that character in the system database and; (2) without any movement of the user's hand, the input slope sequence produced should matched the reference slope sequence, at least one second time frame.

In contrast, *the trial is said to be a failure if*: (1) a character is drawn above the range of the Leap Motion Controller, the system did not recognize the expected character and; (2) the slope sequence generated by the user for a character is different from the reference slope sequence pattern.

III. RESULT AND DISCUSSION

A. Experiment for slope orientation sequence to be used

In analyzing the slope orientation sequence to be used in representing every alphanumeric character, the researchers conducted 25 trials per character and registered the most frequent sequence for each letter as a reference.

Table 3: Slope Orientation Sequence of Alphanumeric Characters

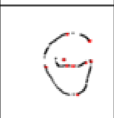
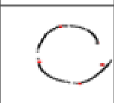
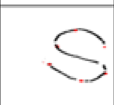
A	[4 8 2 6 1] [4 8 2 6 2] [4 8 2 6 8]	M	[3 7 2 8 3] [3 7 3 8 3] [3 8 2 7 3] [3 7 3 7 3]	Y	[2 8 4] [2 8 4 3]
B	[2 7 2 4 2 4] [3 7 2 4 2 4] [3 6 2 4 2 4] [3 8 2 4 2 4]	N	[3 7 2 7] [7 2 7] [7 3 7]	Z	[1 4 1]
C	[6 4 2 8] [4 2 8]	O	[4 2 8 6] [6 4 2 8]	0	[6 4 2 8] [4 2 8 6]
D	[3 7 2 4] [4 7 2 4] [3 6 2 4] [3 8 2 4]	P	[3 7 2 4] [3 7 1 4] [3 7 8 2 4]	1	[8 3] [7 3]
E	[3 7 1 4 1 4 1] [3 7 1 4 2 4 1] [3 7 2 4 1 4 1] [3 7 8 4 1 4 1]	Q	[4 2 8 6 2] [4 2 7 6 2]	2	[8 2 4 1]
F	[3 7 1 4 1] [3 7 1 4 2] [3 7 1 4 8] [3 7 8 4 1]	R	[3 7 2 4 2] [3 8 2 4 2]	3	[8 2 4 8 4 6]
G	[6 4 2 8 5]	S	[6 4 2 4 6] [6 2 4 6]	4	[4 1 7 3] [4 2 7 3]
H	[3 8 3 6 1] [3 7 3 6 1]	T	[3 6 1]	5	[5 3 8 4 6] [4 3 8 4 6] [5 4 8 4 6] [5 2 8 4 6]
I	[3]	U	[2 8 3] [2 8 7] [3 8 7]	6	[6 4 2 8 6 4] [4 2 8 6 4]
J	[2 4 8] [3 4 6 1] [3 4 7 1]	V	[2 8] [2 7]	7	[1 4]
K	[3 8 4 2] [3 7 8 4 2] [3 8 3 2] [3 7 4 2]	W	[2 8 2 8]	8	[6 4 2 4 6 8]
L	[3 1] [3 8]	X	[2 7 4] [4 7 2]	9	[6 4 2 8 3]

The characters having straight lines have multiple sets of slope orientation sequence; there are at most of 4 sets slope sequence for each. This is due to the way of writing of the user. User tend to draw characters in different sizes with different strokes formed. Also, due to the Leap Motion Controller sensor's sensitivity, straight lines are difficult to achieve. This shows that there is a need to have multiple sets of slope orientation sequence for some alphanumeric characters to increase the system recognition rate. On the other hand, 0 and O have the same slope sequence, to avoid misclassification of characters, the user must use two fingers when drawing numbers and one finger when drawing letters. Letters P and D and, U and V have almost the same slope sequence that leads to misclassification.

B. *Utilizing slope orientation sequence matching*

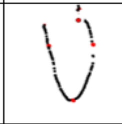
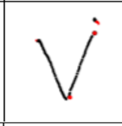
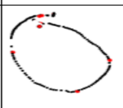
Table 4 and table 5 summarizes the slope orientation sequence obtained from the user's input of characters 2, 3, 5, 6, C, G, J, M, N, S, U and V of the Air-Drawn Alphanumeric Character. The table shows the input alphanumeric character of the user and the slope orientation sequence generated as compared to the slope orientation sequence in the system database.

Table 4: User generated Slope Orientation Sequence for 2, 3 ,5, 6, C, S

Alphanumeric Characters	User Input Gesture	Slope Orientation Sequence Generated	Recognized Alphanumeric Character	Comments
3		[8 2 4 8 4 6]	3	Recognized
5		[5 3 8 4 6]	5	Recognized
G		[6 4 2 8 5]	G	Recognized
2		[8 2 4 1]	2	Recognized
C		[6 4 2 6]	C	Recognized
S		[6 4 2 4 6]	S	Recognized

The characters 2, 3, 5, 6, C and S contains open curves that causes the misclassification from the previous study. As seen in Table 4 the slope orientation sequence established does not rely on the curvature of the character. In contrast, the algorithm interprets the characters based on the slopes formed. For this reason, the system was able to recognize the characters appropriately. In line with this, the recognition rate will tend to increase.

Table 5: User generated Slope Orientation Sequence for U, V, 6, G, O, 0

Alphanumeric Characters	User Input Gesture	Generated Slope Sequence	Reference Slope Sequence	Comments
U		[2 8 7]	[2 8 7] [2 8 3] [3 8 7]	Recognized
V		[2 8]	[2 8]	Recognized
6		[6 4 2 8 6 4]	[6 4 2 8 6 4] [4 2 8 6 4]	Recognized
G		[6 4 2 8 5]	[6 4 2 8 5]	Recognized
0		[4 2 8 6]	[6 4 2 8] [4 2 8 6]	Recognized
O		[4 2 8 6]	[6 4 2 8] [4 2 8 6]	Recognized

Analyzing letters U and V, along with 6 and G, 0 and O, they have almost the same slope orientation sequence generated. This yield is due to the similarity on the features of the characters. Table 5 shows the slope orientation sequence of these characters obtained from the input gesture of the user.

The obtained slope orientation sequence for the 36 Air Drawn Alphanumeric Characters were unique and distinct; hence, used by the researchers to distinguish and recognize them correctly. This satisfies that the Slope Orientation Sequence Algorithm is utilized in recognizing Air-Drawn Alphanumeric Characters.

C. *Acquired reliability of the system*

The researchers conducted ten sets of trials corresponding to five different users that performed the test recognition of the system to determine the reliability of the system in recognizing Alphanumeric Characters. The users performed the character 50 times.

The system recognition reliability was shown in Table 8 and 9 indicating the average recognition rate for every alphanumeric character obtained from result of test recognition performed by the five users. It can be noted that characters 0, 1, 6, 7, 9, C, H, I, J, L, M, N, O, S, T, V, W, X, Y, Z obtained the highest rate which is perfectly 100.00%. This is generally because of the uniqueness of the letters' slope sequence compared to other characters. On the other hand, the lowest recognition rate is 76% which correspond to letter U.

Table 8: Average Recognition Rate for every letter

SYSTEM RECOGNITION RELIABILITY	
LETTERS	Average Recognition Rate
A	98%
B	98%
C	100%
D	86%
E	96%
F	98%
G	96%
H	100%
I	100%
J	100%
K	98%
L	100%
M	100%
N	100%
O	100%
P	78%
Q	94%
R	98%
S	100%
T	100%
U	76%
V	100%
W	100%
X	100%
Y	100%
Z	100%
AVERAGE	**97%**

Since the slope sequence of U and V is almost the same, misclassification arises. In general, the system's reliability in recognizing alphanumeric characters in average is 97%.

Table 9: Average Recognition Rate for every numbers

SYSTEM RECOGNITION RELIABILITY	
NUMBERS	Average Recognition Rate
0	94%
1	100%
2	98%
3	98%
4	92%
5	98%
6	100%
7	100%
8	96%
9	100%
AVERAGE	**97.6%**

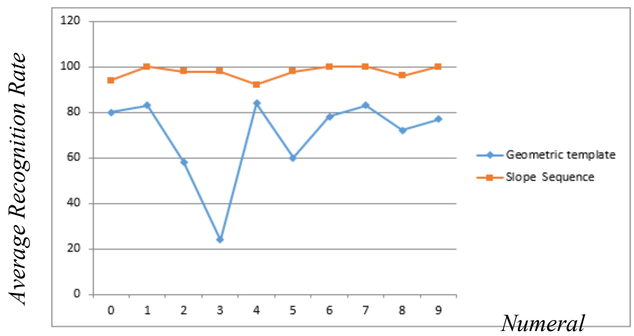


Figure 4: Slope Orientation Sequence vs Geometric Template

The comparison of the accuracy of the recognition rate of numbers commonly misclassified due to their open curves is generally shown in the figure 4. The previous study used geometric template matching. The figure shows the graph of the numbers that achieved lower recognition rate. However, through the application of the proposed algorithm of the researchers, Slope Sequence has significantly increased the accuracy recognition rate of these numbers by 27.4%.

IV. CONCLUSION AND RECOMMENDATION

Based from the gathered data, the slope orientation sequence obtained from the air-drawn alphanumeric characters are distinct. How ever, some of the slope orientation sequences for alphanumeric characters are almost the same. In this context, letters U and V have identical slope orientation sequences as well as letters D and P. Considering the same features of these characters, the generated slope orientation sequence will have no difference. On the other hand, characters containing numerous number of strokes established multiple sets of reference slope orientation sequence, which can be seen on characters 5, B, E, F, K and M. Acquisition of slopes is mainly based in the distance threshold set. The distance threshold is inversely proportional to the number of slopes. As a result, the lesser the distance threshold, the greater the number of slopes acquired; hence, the lesser the slope orientation sequence made. Data also reveals that writing of alphanumeric characters in free air can be recognize by utilizing Slope Orientation Sequence Matching Algorithm. However, the algorithm is dependent on sequence of slopes formed, resulting for the system to be time dependent. Result shows the inconsistency in terms of number of slopes as well as the slope sequence composition of the character. For this reason, the system misclassifies some characters such as E and F that contains multiple strokes. Due to the same motion formed when writing letter U and V, the latter mirrors the slopes formed when writing. This results for the system to misclassify U as V.

The researchers recommend adding other parameters for acquiring the slopes orientation and the determining of the significant part of a character. It must not be mainly based on the distance for reliable resultant slope sequence needed for recognition of Air Drawn Alphanumeric Characters. Likewise, the researchers also recommend adding other algorithm that focuses on time series analysis for better recognition of characters that has the same slope sequence such as O, 0, D, P, U and V. This will improve the utilization of the proposed algorithm.

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