Indonesia Sign Language Letter Interpreter Application using Leap Motion Control based on Naive Bayes Classifier

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Abstract - Most deaf children are born into hearing families and the majority do not begin their Sign Language learning before age 3-6 in school. As children learning Sign Language from infancy show higher language proficiency than those who do not, it underlines the importance of hearing parents learning how to sign. The research method in naïve bayes algorithm, in order to classify 26 alphabet letter of Indonesian sign language including letter J and Z which using gesture for describe it. The Leap Motion controller is a consumer gesture sensor aimed to augment a user's interactive experience with their computer. It use for derive feature data from the deaf children gesture recording to set data in application. The accuracy level of the test result reached 96%.

Keyword : Indonesian Sign Language Letters, Naïve Bayes, Leap Motion Control.

1. Introduction

Persons with disabilities are groups of limitation persons that can hinder their participation in community. Communities that live with limitations are divided into three, namely physical, mental, and both (physical and mental). Examples of physical limitations include blindness, hearing impairment, speech impairment, disability, and other physical limitations.

At present there are a lot of deaf people. In Indonesia, from the Central Bureau of Statistics (BPS) in 2010, there are 3,024,271 million people (the total population in 2010 was 191,709,144 million) experiencing hearing and speech impairment [1].

Based on the results of interviews with several members of the Indonesian Deaf Welfare Movement DPC GERKATIN Makassar, one of the most important things to help with the daily activities of deaf-speech people is to communicate with normal people. Difficulty in communicating will affect the lives and interpersonal relationships in the deaf-mute community. Difficulty in communicating between deaf-mute sufferers and normal people can bring problems in the process of integrating deaf-speech sufferers into the wider community [2].

The sign language used for each country may be different. In Indonesia admit two sign language, the official sign language system used in indonesia is the Sistem Isyarat Bahasa Indonesia (SIBI) where the system is similar to the sigh language applied in the United States, American Sign Language (ASL) and BISINDO used more sign language community in indonesia. In this study using the Sistem Isyarat Bahasa Indonesia (SIBI).

The previous study by Wibowo et al [3] recognize 24 alpahbetic Indonesian letters in Indonesian sign language which resulted in average classfication accuracy for Naïve Bayes is 95%. The inctroduction of J and Z letters cannot record from object because they using gesture for describe letter in indonesian sign language (SIBI). Previous research using the Multilayer Perception (MLP) Neural

Network (NN) method for the introduction of Arabic sign language resulted in an average accuracy of 88%. Then another research using Naive Bayes and Linear Discriminant Analysis (LDA) algorithm resulting in the accuracy of Naive Bayes that is better than LDA, but LDA shows faster time [4]. Marin et al. [5] investigated the performance of Leap Sensors Control by training SVM Classifier to recorgnize 10 different static mark with 1,400 sample counts capable of achieving an average accuracy of 80% as well as research focusing on challenges that include features for accurate signaling cues, and argues on how nomalization to accommodate a reliable system for users with different hand sizes. Chen dkk menggunakan algoritma Hidden Markov Model (HMM) dan Support Vector Machine (SVM) untuk gerakan tangan dinamis. Chen et al.[6] use the algorithm Hidden Markov Model (HMM) and Support Vector Machine (SVM) for dynamic hand movements. Accuracy using the HMM algorithm is 90.56% and SVM is 98.24%. This study detect numbers and alphabets with a total of 36 movements captured by utilizing Leap Motion.

Based on those issue above, an automated system that is usefull as a translation from sign language into written language is needed. The research is based on Classfier Algortihm and sensor Leap Motion Control (LMC), focused on the dynamic alphabet letters and words of Indonesian sign language (SIBI).

2. Material and Method

2.1. Leap Motion Control

Leap Motion is a small device basis of a USB device that can allow a computer user to control or play a computer using motion. In Figure 1, there are two monochromatic cameras with three infrared LEDs in Leap motion. Leap motion captures independent hand movements and finger movements, as well as objects such as pens. In fact, 200x Leap motion is more sensitive than free touch technology in existing products and technologies in 2014. Based on Leap motion has a high detection accuracy so it is widely developed as a controller and also motion recognition.
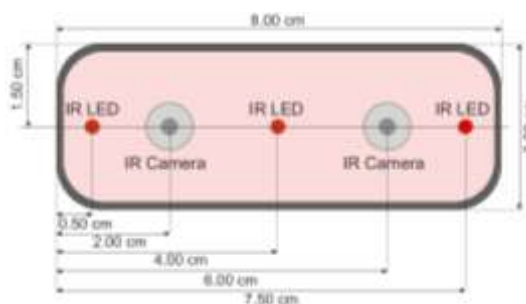

Figure 1. Leap Motion Control schematic

Leap Motion was developed by David Holz and Michael Buckwald. They developed a device similar to Microsoft Kinect but claimed to have a higher level of accuracy. The purposes of David Holz and Michael Buckwald are to replace the functions of the keyboard and mouse and allow users to explore the computer with just finger movements. The Leap Motion works by creating an interactive 4 cubic feet room that is able to detect fingers, hands and arm movements [7]. Data retrieval using Leap motion utilizes API (Application Programing Interface) designed specifically for developers who want to utilize Leap motion [3].

The Leap Motion Sensor controller device accompanied by API support from its provider. Through API support, the hand and finger data can be sent to the person who created the program to use the sensor as an alternative computer interface tool. Table 1 lists the feature of the hand and fingers obtained

from the APIs in this study. Feature of a normal palm (vector uni direction), and speed (in millimeters per second). The LMS API also handels behind-the-scenes image analysis, reducing complex extracting features task of developer from raw input data. This allows research to focus more on feature selection, not the extraciton process. Bellow are accuracy result of applying machine learning to different signification classfication [3] .

Table 1. Features obtained from LMC API

	PALM		FINGERS	
	Name	Type	Name	Fingers
Hand Features*	Normal	Vector	Direction	Vector
	Position	Vector	Length	In mm
	Velocity	Vector in mm/sec	Tip Position	Vector
	Confidence	a float in [0,1]	Tip Velocity	Mm/sec
	Pinch Strength	a float in [0,1]	Dip Position	Vector
	Grab Strength	a float in [0,1]	Pip Position	Vector
	Sphere Center	Vector	Mcp Position	Vector
	Sphere radius	In mm		

2.2. Naïve Bayes Classfier

The bayesian theorem provides a way to calculate the posterior probability based on assumed prior probabilities and the probability of different data object under given assumptions. Bayesian algorithm based on bayesian theorem is a simple and commonly used classification algorithm which has rigorous mathematical theories as a basis. Assuming each attribute of the items to be classified is independent of each other, the constructed classification algorithm is naïve bayes. The basic idea of naïve bayes is: for a given item to be classified, calculate the probability of each category which the item belongs to, and the item will belong to the category with the largest probability [8].

The Bayesian classification approach is based on quantifying the trade-offs between various classification decisions using probability and the costs that accompany such decisions [9]. The classifier was developed based on Bayes probability rule which states:

$$P(Y|X_1, ..., X_n) = \frac{P(X_1, ...X_n|Y)P(Y)}{P(X_1, ...X_n)}) \qquad (1)$$

This is the probability of obtaining Y given conditions X1toXn or the posterior probability of Y given a prior probability of Y and X1toXn likelihood. In our case, using the letters, this is interpreted as posterior probability of any letter given the likelihood parameter and a prior probability of that letter. The decision is taken based on the greatest of the calculated probabilities to achieve minimum error classification [9]. From the Bayes rule, the NBC is mathematically stated as:

$$P(X_1, ..., X_n|Y) = \prod_{i=1}^{n} P(X_i|Y) \qquad (2)$$

2.3. Euclidean Distance

Euclidean Distance is the classifier that is most often used to calculate the similarity of 2 vectors. If the distance between 2 images is large, then it can be concluded that the two images are not similar,

whereas if the distance between two images is small, then the image is similar [10]. The equation of the euclidean distance is.

$$d_{ij} = \sqrt{\sum_{n-1}^{k}\left(x_{ik} - x_{jk}\right)^2} \ldots\ldots\ldots\ldots\ldots\ldots\ldots. (3)$$

2.4. Feature Extraction

Leap motion produces sensor data in the form of the position of each hand and finger joint when there is a hand moving in the sensor capture room. These data are formed into a vector model which is then stored in the database as reference data. Each movement will be compared with this reference data to detect what the movement means.

In an initial attempt to create sign recognition software, using video analysis, the main challenge was not a feature that had to be put forward, but extraction itself. However, in the case of Leap Motion, the API provides a framework with a skeleton model for each hand, and reduces individual developers from heavy duty to analyze IR images to get relevant information [3].

Each hand object is built from the finger and the object of the palm, and each finger is formed by a set of bones. Each object has an appropriate 3-dimensional vector, referring to its direction and position in the euclidian space in the sensor display.
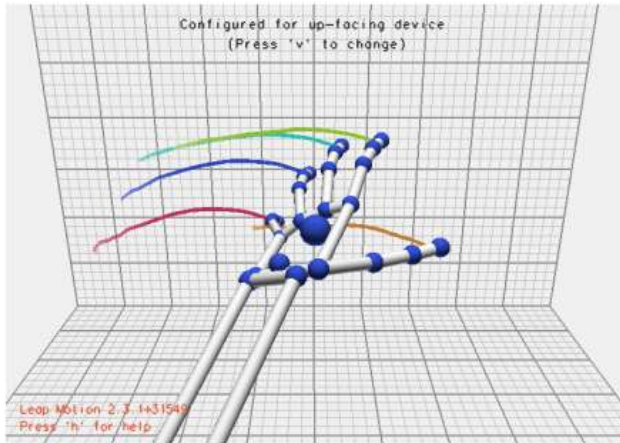

Figure 2. LMC Framework Model

Dynamic features are dynamic motion features or features obtained from LMC detection of the hands [11]. The good feature formation will increase accuracy in sign language recognition. The features used are Distal Tips Fingers, Palm Direction and Palm Position .
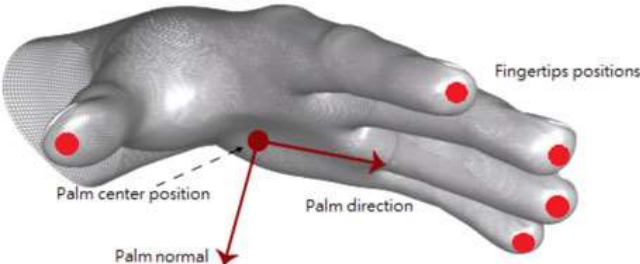

Figure 3. Hands Features

2.5. Data Acquistion

There are 26 letters of indonesian sigh language Alphabet (SIBI) used in this case static and dynamic as show in figure 4. The total number of training use totals 1300 samples derived from 50 samples for each letter class of 26 alphabet sourced letter from 5 different hand respondents where each respondent made 10 training data.

Figure 4. Sign Language Indonesia (SIBI) Alphabet

In this paper the initiate time of capture is base on leap motion first time frame caputre and while leap motion capture hand gesture time. The tools used for thisl data capture was written with referencing to controller SDK using Python.

3. Desain System

System design consists of two main parts, namely the application of data training or builder and application of data testing. The training data application is used to record the user's hand movements without having to learn about programming languages first. Besides it can be used to store data into a dataset and can extract data from datasets into vector shapes that will be used for classification processes. The interpreter application is used as a user interface to learn sign language. The interpreter application is connected to Leap Motion Service runnning with the Leap Motion API.
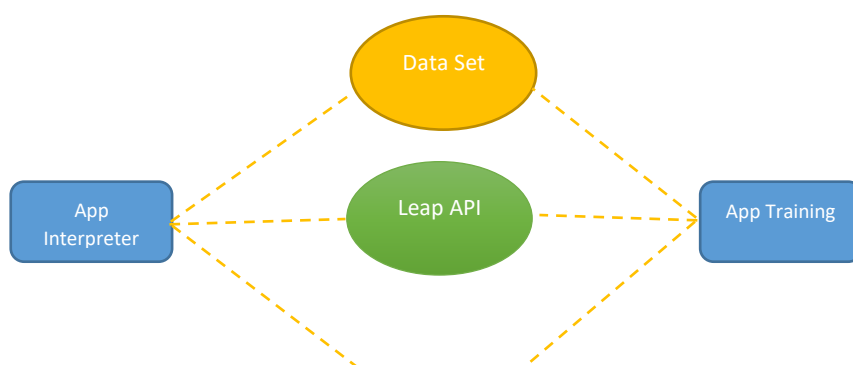
Figure 5. System Design

In the data training process, the vector data was obtained from the results of feature extraction by SDK Leap Motion and then data normalization was carried out on the three data items obtained from the reading of leap motion control namely Vector fingers, hand patterns or rolls and palms. Normalization of data on the fingers with the following formula :

$$Normalisasi = F_i - C \dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

Fi is the coordinates of the fingers of each hand,
C is the coordinates of the position of the palm.

In the extraction stage, the hand direction feature is only made to change the value to degrees because the data obtained from the API Leap Motion is a Radian value. The formulas used at this stage are:

$$\deg = rad * 180/\pi \dots\dots\dots\dots\dots\dots\dots\dots\dots(5)$$

Whereas the process of test data is almost the same as the training data process, the difference lies in the last process where the training data process saves data to the dataset, while the test data process converts data from continuous data into discrete data using the Naïve Bayes Gaussian approach.

4. Classifier

This research used Naive Bayes for its basic classifier. This classifier was chosen due to its simplicity in technique and implementation. The basic principal of Naïve Bayes is assuming every feature in the feature-sets is not dependent each others. Its efficiency in using the data training, by using a small amount of data-set without reducing the accuracy of classification performance makes this classifier widely used on many gesture recognition researches [12].

Basically, Naive Bayes is a statictical approach with the probability formula as follows:

$$P\big((C_k|x)\big) = \frac{P(C_k)P\big((x|C_k)\big)}{P(x)} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots..(6)$$

In order to naïve bayes the classifier can work at discrete values, one of which can assume a Gaussian distribution for each feature above all samples in the feature vector. So the probability of the feature x entering a class is

$$P(x|c) = \frac{1}{\sigma c \sqrt{2\pi}} e^{-\frac{(x-\mu c)^2}{2\sigma_c^2}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(7)$$

Probability calculations often get a small number, and multiplying them together will risk losing precision. To overcome this, the logarithm of all three parts of the equation is taken, resulting in a formula

$$log\big(P(c)\big) + log\left(\frac{1}{\sigma\sqrt{2\pi}}\right) - \frac{(x-\mu)^2}{2\sigma^2}\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(8)$$

Calculation of euclidean distance is used in samples of average values using formulas ;

$$d(p,q) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2}\dots\dots\dots\dots\dots\dots\dots\dots(9)$$

Simply classification of vectors based on the highest probability of all class probabilities :

$$\max_i\big(P(c_i)\sum_j^k P(x_j|c_i)\big)\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots(10)$$

5. Experiment and Result

Base on the stage shown in the system design, the system development as a result of this writing can be seen in figure 6 as app data training and figure 7 AppInterpreter, for the recognition of indonesian sign language pattern using leap Motion Control and Naïve Bayes.
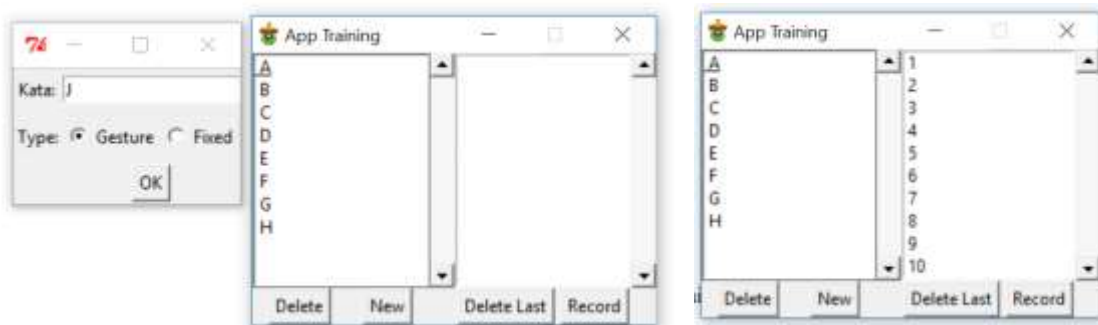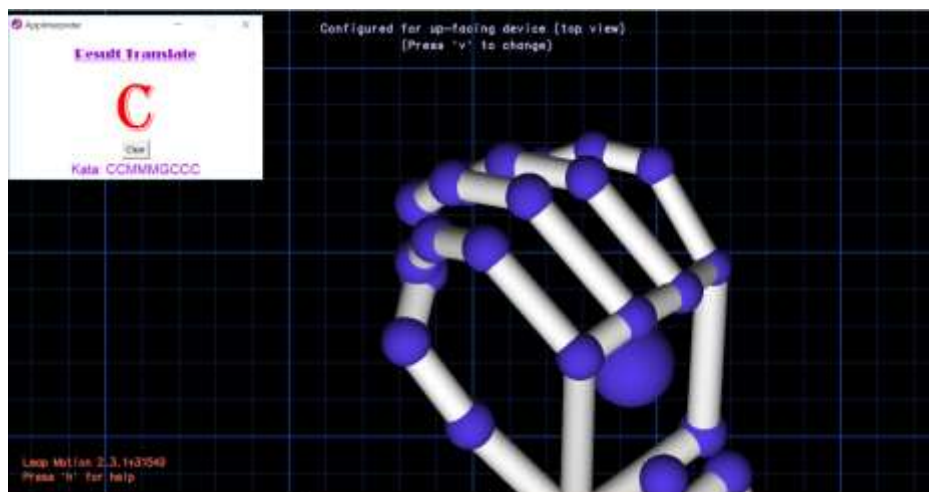

Figure 6. Result App Data Training

Figure 7. App Interpreter

5.1. Experiment

Using a tool titled as Tkinter (GUI of Python) for presenting and evaluating the classifier method base on model generated from feature-sets which is formatted on P file. Python already the default naïve bayes classifier as well, so that we just need import library from scikit.

The research tried to classify the gesture using gesture classficiation for leap motion, we classifying the 26 letters of indonesia sign language (SIBI) using the hand of the respondents. Through the testing proces with the loop count 6 times to test the 26 letters of SIBI alphabet consist of A, B, C, D, D, F, G, H, I, J, K, L, M, N, O, P, Q, R, S, T, U, P, W, X, Y, Z. Total data set amounted 156 samples and the respondent's distance hand to the leap motion sensor device are 12 cm. this data classify using naïve bayes algorithm.

5.2. Result

Classifcation result showed on the table 2, where are letters known as another letter because pattern or gesture same other letter. For example, N recognized as M or N.

Table 2. Classification Result

Alphabet	Experiment		Known As other Letter
	True	False	
A	6	0	
B	6	0	
C	6	0	
D	6	0	
E	6	0	
F	6	0	
G	6	0	
H	6	0	
I	6	0	
J	4	2	I
K	6	0	
L	6	0	
M	6	0	
N	4	2	M,O
O	6	0	
P	6	0	
Q	6	0	
R	6	0	
S	6	0	
T	6	0	
U	6	0	
V	6	0	
W	6	0	
X	6	0	
Y	6	0	
Z	4	2	U,L

Table 3. Leap Motion Classification

Result Of	Samples	Percent
Correctly Classified Instance	150	96,16 %
Incorrect Classified Instance	6	3,84 %
Total Instance	156	

Fiture extraction and data normalitation for data testing from Leap Motion API same with training data processing. Testing data take from 17 frame with contain XYZ finger distal, pitch and roll coordinate. Classification result shown on the table 4 which data shorted from the highest probability to low probability. Beside determined from probability level, so determine from euclidean distance. If there are alphabet had highest probability value and the closest distance between training data with tesing data then found the valid data.

Table 4. Probability count result of each class

Class	Probability	Euclidance
A	0.49829063002951625	0.12427167771365978
T	0.4964730754720572	0.6618753674332744
M	0.4964615506098093	0.9584814326190543
S	0.4964276936817576	0.4256425352416988
N	0.49626077181041944	1.0204044337833829
P	0.4946699394927318	1.4140232621574138
X	0.49443004115831723	0.597754565193763
Q	0.4938637754273052	1.5787214251343185
Y	0.49381156705336626	1.261124779865341
J	0.49377800601617323	1.461864793829387
O	0.4934157826912663	0.913767149405667
I	0.49287800601917325	1.0242695823042858
E	0.49177978614464	1.278849553767374
H	0.4911575131250296	1.350758627322214
Z	0.4910607418904194	1.121487434075456
C	0.49095721853010466	1.2303544651418814
G	0.4899545038668552	1.333429433914674
V	0.48961781454498543	0.8201949635276955

D	0.4890006075788114	0.5960133709134533
L	0.4885066079953518	1.094546589476957
R	0.48437733856275167	0.5770244486141277
W	0.4803115273695701	1.4605308147142804
U	0.47989742792023293	0.8555228250937538
K	0.47855049630856755	1.208564425582325
F	0.47749830469325505	1.1384021651862253
B	0.22240801991810477	1.4040570409006827

Based on table 4, probability values from A letter is great, and also have closest distance so that classiffication result of A letter is valid

5.3. Discussion

As shown on the table classificattion result above (table 2) there are letters rocognized as another letter. For instance N recognized as M and O, Z recognized as U and L, J recognized I. the main problems from their shapes resembles the position cordinate and finger figure one to another on this study. For get training data, please do be carefully because can influence result of the data classification. As shown on the table Leap Motion Classfication most of gesture and fixed classification generate above 96 %. During leap motion usage, it is frequently failed to recognize the hidden fingers considering its hardware limitation from sensor view. The mistake could accour because no macth data from respondent with data from leap motion API. The real finger shown versus the finger are in the model API skeleton are different on the screen.

5.4. Conclusion

In this paper, Dynamic Hand Recognition for Indonesian Sign Language (SIBI) using Leap Motion Control approaches has been proposed Eeulidean Distance and Naïve Bayes as a method for get the high accuracy. The experiment result, show increase accuracy until 96% with gesture and fixed hand. As the future work, it can combine two sensor for get more accuracy and combine more methode or algorithm.

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