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19–20 September 2020

Universitas Dian Nuswantoro Semarang

PROCEEDINGS

2020 International Seminar on Application for Technology of Information and Communication

(iSemantic)

IT Challenges for Sustainability, Scalability, and Security in the Age of Digital Disruption

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~~Submission Deadline (Extended)~~	~~June 30, 2020~~
Notification of Acceptance	July 20, 2020
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Conference	19, 20 September 2020

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ISEMANTIC 2020 KEYNOTE SPEAKER PRESENTATION can be downloaded here (TBA).

Information

COVID-2019 Update - iSemantic 2020 Conference will be held with Online Seminar and Parallel Session due the WHO has characterized as 'Global Pandemic'.

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Silhouette Analysis of Hand Gesture Dataset Using Histogram Profile Feature Extraction

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***Abstract*— Hand gesture dataset is a collection of hand gesture images. Several hand gesture datasets are freely available and can be used for various purposes, such as comparison or method testing. Processing the distribution of hand gesture image quality in the dataset has the opportunity to find potential models of hand gesture image quality for further research. This study tries to provide answers by exploring the quality of hand gesture images based on various datasets of public hand gestures. Then perform feature extraction based on the image histogram profile to get an overview of the range of color intensity values from the hand gesture image. The Herarchical Clustering method is used to build clusters based on histogram characteristics. The feasibility of the relationship between clusters was tested based on the silhouette index clustering method. The total number of hand gesture test images is 16 thousand data taken from 6 dataset sources that have been used in hand gesture recognition research. Based on the results of the processing, it is shown that the three clusters have no relationship feasibility or in other words the image clusters are independent.**

Keywords—hand gesture; feature extraction, histogram profile; herarchical clustering; silhoutte index

I. Introduction

Gestures are symbols of communication that are expressed through movement of the limbs and are generally used as natural non-verbal communication media by humans. One of the most dominant body parts used as a non-verbal communication gesture is the hand [2]. This hand gesture can be read or read either in personal activities (scratching the head, cleaning the nose or ears, covering the nose, rubbing the eyes etc.) or as a medium of communication with other objects. This is certainly very interesting to study considering that human-computer interaction media technology using hand gestures has the potential to be applied in the future era.

The quality of hand gesture data in the hand gesture recognition process is very important. Data quality is so important that some researchers have demonstrated hand gesture recognition efforts by observing the devices used to capture the data. Some of the potential hand gesture data capture devices that have been studied include the use of gloves [3], the opportunity to use radar devices [7], data capture devices using infrared [5], wifi devices [1] and audio frequencies [4], however, camera devices became more popular.

Al-Shamayleh [12] in his literature study explained that the camera device is a device that is popularly used to capture hand gesture data (77.2%). Considering this, the dataset processed in this study is a dataset that uses a camera device as a hand gesture data capture device and outputs an RGB image.

Currently, there are quite a lot of public datasets of hand gesture RGB images available. The next question that arises is: What is the distribution of the visual quality of hand gestures based on the available hand gesture RGB image dataset? The answer to this question is expected to provide information on the visual quality area of hand gesture images that are rarely used as test data.

In fact, the above questions can be quickly answered by knowing the image histogram. The presentation of an image histogram as another way to view a digital image is actually a common practice, especially by image processing actors. Through the image histogram, the color distribution in the RGB value of the pixels can be clearly identified. Unfortunately, this can only be done if the number of images to be observed is not very large. Conversely, if the amount of image data reaches thousands, it is necessary to formulate adequate steps to obtain information on the distribution of visual quality based on the large amount of image data.

In this study, 6 stages of the process were formulated to obtain information on the distribution of hand gesture RGB image quality based on selected public datasets. The six stages of the process are: dataset collection, histogram profiling, feature extraction of the histogram profile, clustering and silhouette index. The process at the clustering stage is expected to provide information on the quality model of hand gesture images that have been used. Through the silhouette index process, it is expected that the potential models of hand gesture image quality can be found that have the opportunity to be investigated further.

The explanation in this article is organized into 4 parts, namely: an introductory section that describes the problem description and the steps for the solution approach, the method section that describes the details of the method at each stage of the process, the testing section displays the test results and the analysis section shows the discussion of the test results.

The expected contribution of this research is the emergence of information on the distribution of hand gesture image quality models that have been studied as well as information about the potential for hand gesture image quality models that are rarely studied. Through this information, the problem can be further investigated to find a solution approach.

II. Histogram Image Hand Gesture

A digital image histogram is another way of presenting an image that is displayed in a graphic format. The role of the digital image histogram is very important in the process of improving the quality of digital images. Apart from being used to see an overview of a digital image, image histograms are also used to perform the digital image engineering process.

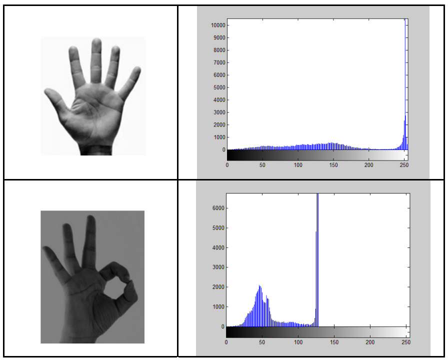

Fig. 1. Example of a histogram of a hand gesture image

An image histogram is built based on the frequency of appearance of the color intensity value of a point in the image [6]. The more often a color intensity is used, the higher the frequency value will be and vice versa.

The digital image histogram presents information as is from a digital image because the image histogram works by counting the appearance of a color intensity of a pixel point in the image. The histogram presentation based on 2 different image quality is shown in Fig. 1.

III. Dataset Hand Gesture

The RGB image hand gesture dataset is a collection of image data in the form of an RGB-based hand gesture image. Hand gesture image data is obtained through a hand gesture data capture device and has been adjusted to the needs of the case to be studied.

The public hand gesture dataset is clearly quite helpful for researchers who wish to conduct tests or make comparisons of hand gesture recognition methods.

Fig. 2. Sample from Cambridge-Hand Gesture dataset used by T-K. Kim [8]

An example of hand gesture image data from a hand gesture dataset that has been used in a hand gesture recognition study is shown in Fig. 2. Several popular hand gesture datasets are used, including: the Cambridge-Hand Gesture dataset from Cambridge University used by T-K. Kim [8], ASL FingerSpelling Dataset from the University of Surrey's Center for Vision, Speech and Signal Processing used by Brandon Garcia [10], GTI dataset from Universidad Politécnica de Madrid used by Maqueda [11] and ASL dataset. from the IEEE Dataport used by Raimundo [13].

IV. Proces Stages

A. *Procesing Steps*

The silhouette analysis process in the hand geture dataset involves several process stages, which are interrelated with one another from start to finish. Next, take the assumption that hand gesture data from datasets are already available, then the following is shown in Fig. 3. is the flow of the process stages.

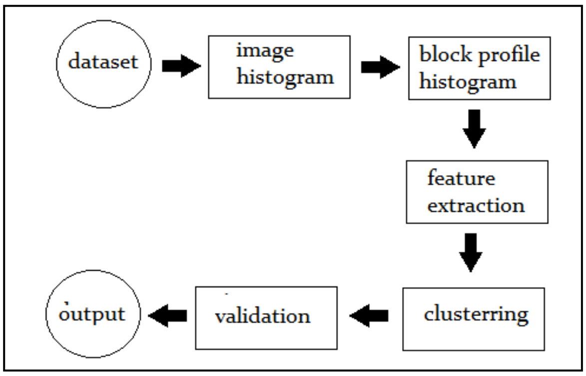

Fig. 3. Steps of silhouette validation

B. *Feature Extraction of Histogram Profile*

This process is carried out after the histogram of a gesture image is available. It is called a histogram profile because each hand gesture image is considered unique so that each histogram will represent its image profile.

At this stage, a feature extraction step is formulated to find the feature points from the histogram of the hand gesture image. Feature extraction is done by dividing the total color intensity range on the histogram into several groups of color intensity ranges. Taking into account that the features must represent the facts as closely as possible the sublocks of the intensity range are further divided into several narrower measures. Finally, a representative characteristic value of the range of intensity is obtained based on the narrowed sub-block profile.

Furthermore, considering that the intensity of color or tone is an important factor in image presentation, the distribution of the profile blocks is decided based on 5 tone areas, namely: dark, light dark, middle tone, light bright, bright, as shown in Fig. 4.

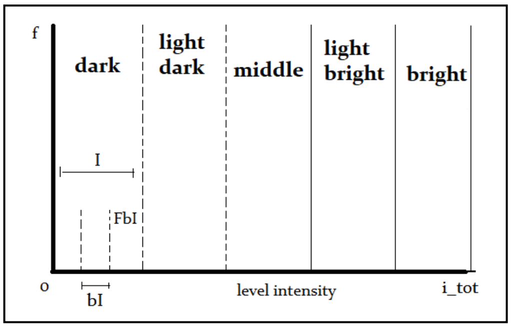

Fig. 4. Block profile for feature extraction proces.

Below is an explanation of the illustration in Fig.4 and the computational formula for its feature extraction.

$$I = \frac{i\_tot}{5}, i_{tot}: total\ intensity \quad (1)$$

$$bI = \frac{I}{3} \quad (2)$$

$$\overline{bI} = \sum_{i=1}^{n} bI_i \quad (3)$$

$$FbI = \overline{bI} \quad (4)$$

where, I is size each block, bI is size each subblock, $\overline{bI}$ is an average point of subblock I, FbI is anextraction point of subblock.

Factors related to the frequency of occurrence of a color intensity are considered negligible considering that frequency only has a strong relationship on image size and not on image color quality.

C. Agglomerative Herarchical Clustering

Cluster formation using the Agglomerative Hierarchical Clustering (AHC) method was chosen considering the size of the unknown group. Here are the computational steps of the AHC method:

1) Calculate the distance between data matrices
2) Combine the two closest groups based on the defined proximity parameter
3) Update distance between data matrix to represent the closeness between the new group and the remaining groups
4) Repeat steps 2 and 3 until only one group remains

The calculation of the distance matrix in this study was carried out using the Manhattan method through the computations shown in formula 5.

$$Dm = \sum_{I=1}^{n} |b_i - a_i| \quad (5)$$

Furthermore, considering that the image histogram profile blocks are formed sequentially and adjacent to one another, it was decided that the cluster approach was tested using the average linked method. The computation is shown in formula 6 below.

$$d_{uv} = average\{d_{uv}\}, D_{uv} \in D \quad (6)$$

D. Silhouette Coeffisient as Cluster Validation

Silhouette Index (SI) is used to validate a single data, single cluster, or even an entire cluster. This method is widely used to validate clusters that combine cohesion and separation values [13]. The SI value ranges from -1 to +1. SI values close to 1 indicate that the data is right in the cluster. SI is 0 or close to 0, then the position of the data is on the border of the two clusters.

$$a_i^j = \frac{1}{m_j - 1} \sum_{r=1}^{m_j} d(x_i^j, x_r^j),$$
$$i = 1,2,..,mj \quad (7)$$

$$b_i^j = \min \left\{ \frac{1}{m_n} \sum_{r=1}^{m_n} d(x_i^j, x_r^n) \right\},$$
$$i = 1,2,..,m_n \quad (8)$$

$$SI_i^j = \frac{a_i^j, b_i^j}{\max\{a_i^j, b_i^j\}} \quad (9)$$

$$SI_j = \frac{1}{m_j} \sum_{i=1}^{m_j} S_i^j \quad (10)$$

$$SI_j = \frac{1}{m_j} \sum_{i=1}^{m_j} S_i^j \quad (11)$$

Where, ai is the average distance of the ith data to all other data in a cluster; bi is the average distance between the ith data to all data from other clusters, then the smallest data is taken; $d(xij, xrj)$ is the distance between the ith data and the rth data in one cluster j, while mj is the amount of data in the j-th cluster; k is the number of clusters; $SIij$ s the Silhouette Index formula; SIj is the SI for each cluster; SI is SI global.

The following is a measure of silhouette value according to Kaufman and Rousseeuw [13]. Silhouette coefficient (SC):

a. 0.7 < SC <= 1, strong structure

b. 0.5 < SC <= 0.7, medium structure

c. 0.25 < SC <= 0.5, weak structure

d. SC <= 0.25, no structure

V. Results and Discussion

This study uses test data from public datasets, namely 5 sources of hand gesture datasets (Table I.) with a total test data of 16303 test data from various public datasets..

TABLE I. LIST OF DATASET INPUT

No.	Dataset Name	Num. input
1.	Cambridge Hand Gesture	1080
2.	Hand Gesture GTI	4618
3.	Kaggle Hand Gesture	1699
4.	Sign Language MNIST	1750
5.	Quan Yuan Hand Gesture (part 1,2 and 3)	4456
6.	Google.github Media Pipe Hand	2700

After the testing phase is carried out, a cluster group is obtained where each cluster provides an estimated visual status of the hand gesture image. Based on the dendogram shown in Figure. 5 note that the test results show the grouping of the visual status of hand gesture images into 3 clusters. Given that the data set source is 6 and the test results show 3 clusters, there is a possibility that 3 datasets have high similarity so that they are clustered into one.

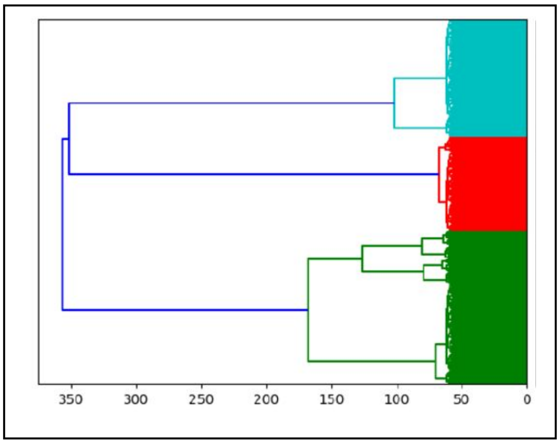

Fig. 5. Dendogram result of clusterring proces

TABLE II. RESULT OF SILLOUTTE INDEX

SI Clustter	0.56	04.8	0.34
SI Global	0.49		

Furthermore, the relationship level between clusters is tested using the silhouette index method to find the coefficient value that indicates the level of the relationship between the clusters. Table II shows the coefficient value of the correlation level test results between the 3 clusters. The more the coefficient value approaches 1, the greater the relationship between the clusters and this shows that the gesture image data inputs in the cluster are often used for research data. Conversely, the lower the coefficient value, the more it shows a strong dichotomy or a high level of cluster isolation.

Based on the size of the SI value in Table II, it is shown that it is 0.56 (C1), 0.48 (C2), 0.34 (C3). According to Kaufman and Rousseeuw, the first cluster of 0.56 (C1) is included in the medium structure, while the second cluster (C2) of 0.48 is included in the weak structure, and the third cluster (C3) of 0.34 is included in the weak structure. The global SI value of 0.49 is also included in the weak structure.

VI. CONCLUSION

Considering the results of the sillouette index which are in a weak structure status, it can be concluded temporarily that the three image clusters, namely C1, C2 and C3 have an inappropriate relationship or in other words, the image is independent. The three independent clusters inform the estimated number of clusters or distribution based on the visual image quality of the hand gesture datasets.

Based on the above, it is planned for the next research to dig deeper into visual quality information based on the number of distributions found, increase the number of public hand gesture datasets and try to modify the feature extraction method to increase the findings of the histogram profile pattern while trying to make comparisons with other cluster methods such as K -Mean.

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