Bag-of-Visual-Words Model for Fingerprint Classification

Pulung Andono and Catur Supriyanto
Department of Computer Science, University of Dian Nuswantoro, Indonesia

Abstract: *In this paper, fingerprint classification based on Bag-of-Visual-Word (BoVW) model is proposed. In BoVW, an image is represented as a vector of occurrence count of features or words. In order to extract the features, we use Speeded-Up Robust Feature (SURF) as the features descriptor, and Contrast Limited Adaptive Histogram Equalization (CLAHE) to enhance the quality of fingerprint images. Most of the fingerprint research areas focus on Henry's classification instead of individual person as the target of classification. We present the evaluation of clustering algorithms such as k-means, fuzzy c-means, k-medoid and hierarchical agglomerative clustering in BoVW model for FVC2004 fingerprint dataset. Our experiment shows that k-means outperforms than other clustering algorithms. The experimental result on fingerprint classification obtains the performance of 90% by applying k-means as features descriptor clustering. The results show that CLAHE improves the performance of fingerprint classification. The using of public dataset in this paper makes opportunities to conduct the future research.*

Keywords: *Fingerprint classification; bag of visual word model; clustering algorithm; speeded-up robust feature; contrast limited adaptive histogram equalization.*

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1. Introduction

Nowadays, the development of biometrics application is growing because of security problem and forensic reason. The purpose of biometrics identification system is to recognize the identity of a person by their face, voice or fingerprint. For security purpose, biometrics system can unlock the door. It may also be used to recognize a criminal from Closed Circuit Television (CCTV). For forensic reason, it is used to identify an accident victim. Biometrics is preferred compared to traditional identification system, such as password or Personal Identification Number (PIN). Fingerprint is a biometrics identification system widely used for human identification [22]. The pattern of fingerprint of each person is unique, which is impossible that an individual has identical fingerprints [15]. Therefore, fingerprint is very popular for personal identification system.

Generally, fingerprint recognition research area studies on fingerprint verification and identification [5]. The objective of fingerprint identification is more complex than fingerprint verification, which is fingerprint identification need to identify a query fingerprint in the collection of fingerprint database of different person [5]. Otherwise, fingerprint verification is used to decide that two fingerprint images are the same or not [6, 16]. A large number of fingerprint database raise the problem of computational time in fingerprint recognition. Many researchers use classification and indexing technique to overcome it [12]. They use classification to identify the pattern of fingerprint. It is used before fingerprint verification or identification. This classification reduces the space complexity of fingerprint recognition. Commonly, the classification is based on Henry's classification which comprises of eight classes: plain arch, tented arch, left loop, right loop, plain whorl, central-pocket whorl, double loop whorl and accidental whorl [1].

Few previous studies research on fingerprint classification in which the individual is the target of classification. Do *et al.* [4] uses many number of classes in their research. However, the experiment uses private dataset. It causes difficulty to evaluate for research community. Balti *et al.* [2] proposed back propagation neural network for fingerprint verification based on minutiae approach. However, the method fails on the small number of minutiae [20].

Bag-of-Visual-Word (BoVW) is a new trend technique as feature extraction in pattern recognition [3, 9, 23, 25]. In BoVW model, each image has a set of visual words which is built by clustering the local feature descriptor of the images. Commonly, Scale Invariant Feature Transform (SIFT) or Speed-Up Robust Feature (SURF) is used to extract these features. Related to BoVW model, He *et al.* [7] presented fast fingerprint retrieval technique based on bag of visual word. They used *k*-means to cluster the descriptor. Each descriptor is indexed by Locality-Sensitive Hashing (LSH). Their work evaluated some of descriptor methods such as SIFT, SURF-128, SURF-64 and DAISY for fast fingerprint retrieval.

Prior research in BoVW-based fingerprint classification, there is no evaluation of the clustering algorithm to construct visual words. This leads to our first research question: which clustering algorithms produce the high quality cluster? Second, related to the quality of fingerprint images, how effective of the image quality enhancement for BoVW-based fingerprint classification? Since, in some devices lead the low quality of fingerprint images. To overcome this problem, we propose Contrast Limited Adaptive Histogram Equalization (CLAHE). It works well on minutiae-based fingerprint identification [18, 19]. Image quality plays an important role in improving the fingerprint recognition [14].

The design of fingerprint classification framework will be the main contribution of this paper. Our experiment uses public dataset FVC2004 in which the individual person is the target of our classification. This paper contains of five sections, the first being introduction. Section 2 presents related work. Section 3 presents our proposed technique. Experiment and result are presented in section 4. Finally, the conclusions of this paper are presented in section 5.

2. Related Work

As discussed above, our related papers work on BoVW based fingerprint classification. Currently, there is limited work focused in that research. Do *et al.* [4] raised the issue of the large number of visual words. They proposed random forest of oblique decision trees to deal with the high dimension of the fingerprint images.

Another work is He *et al.* [7] that proposed fingerprint indexing and retrieval based on BoVW. They evaluated several feature descriptors to produce the visual words. The experiments show that SURF-128 perform better than others.

3. The Proposed Technique

In this proposed fingerprint classification, keypoint descriptors are extracted from fingerprint images. These descriptors are used as features in fingerprint classification. Figure 1 illustrates the flowchart of proposed fingerprint classification. There are five steps:

1. Image quality enhancement.
2. SURF descriptor extraction.
3. Clustering image descriptor.
4. The construction of BoVW.
5. Classification.

3.1. Image Quality Enhancement

CLAHE [17] is an extension of the Adaptive Histogram Equalization (AHE) where the image is divided into small regions called tiles. These tiles are then individually enhanced using histogram equalization. CLAHE overcomes the problem of homogeneous of the area. High pick of the histogram means that the area is homogeneous. CLAHE uses clip limit at the predefined value to prevent over saturation of the image. High number of clip limit indicates that the image would be more contrast. In this paper the image is divided into 64 regions (8×8 blocks).

3.2. SURF Descriptor Extraction

Our proposed framework uses SURF [13] as local descriptor to define the features for classification. Although, SIFT is more robust to noise and illumination change. SURF is more power to distinguish the characteristic of an object and faster than SIFT [8]. In the case of features number, we define SURF-128 and SURF-64. A total of 128 or 64 features length is extracted for each descriptor. An image maybe have large number of descriptors. These descriptors can be used to describe the characteristic of the area around keypoints [7].

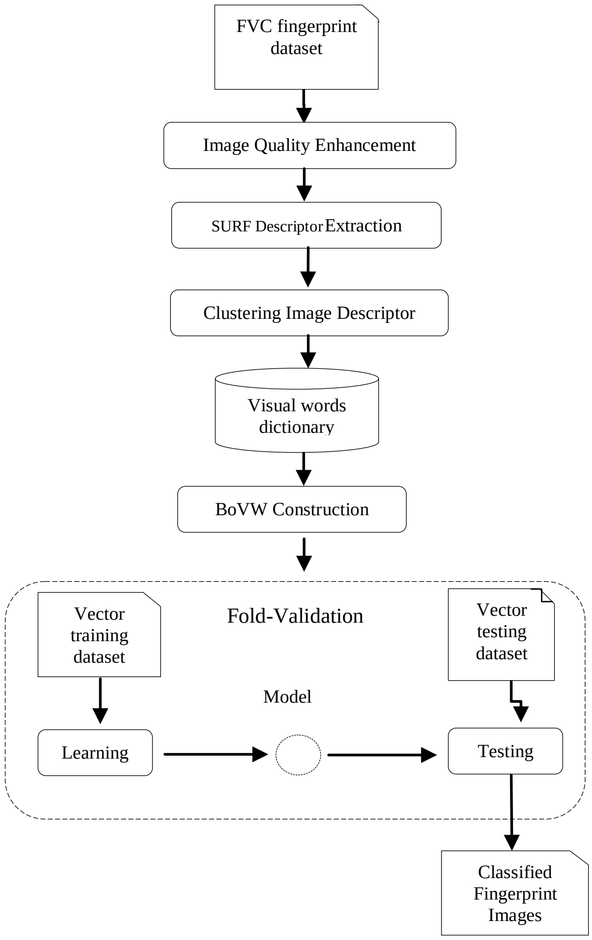


Figure 1. Implementation flowchart of proposed fingerprint Classification.

3.3. Image Descriptor

We use *k*-means [10], *k*-medoid, hierarchical agglomerative clustering and fuzzy c-means to cluster the descriptors. These algorithms have the same characteristic which need to initialize the number of cluster. The number of descriptor in each image is vary. In our work, these descriptors are clustered into several number of cluster *k*=10, 25, 50, 100 and run the algorithm 3 times. The centroid of a cluster will be a codeword or visual word vocabulary. The number of cluster is the vocabulary size. Most of researchers apply *k*-means to cluster the descriptors [4, 7, 21, 23, 24]. It will be a research opportunity to evaluate these algorithms in BoVW model.

3.4. BoVW Construction

In this step, we have bag of visual word vocabulary stored in database. The fingerprint images is represented by the histogram of codeword. The length of vector of each image is equal to the codeword size. Figure 2 shows the scheme of BoVW construction. We use all images to construct the vocabulary. Then, we split the images into training and testing images.

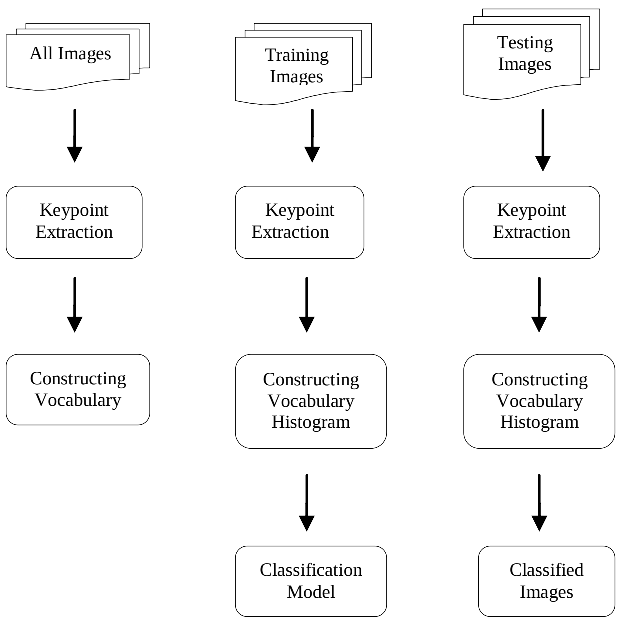


Figure 2. Bag-of-Visual-Words Model Scheme.

3.5. Classification

Our proposed technique applies Back Propagation Neural Network (BPNN) to classify the finger images. BPNN is widely used and perform better than other classification methods. This algorithm consists of three types of layers. There are input, hidden and output layer. The number of node in each layer is vary. The input layer may have one or more node depend on the input data. The structure of BPNN may have one or more hidden layer and the number of node in each layer usually is more than input and output layer. The third layer is output layer, with two or more node for the classification problem.

BPNN is a supervised machine learning algorithm that used to predict or classify sets of data. Network parameters need to adjust to produce high accuracy, such as connection weight, activation function, learning rate, momentum, and training cycle.

4. Experiment and Result

4.1. Experimental Setup

In this section, four fingerprint databases from FVC2004 set B [11] are used to evaluate our proposed fingerprint classification. Each containing 80 images from 10 individuals.

Table 1. FVC 2004 database description.

	Sensor Type	Image Size	Number of images	Resolution
DB1_B	Optical Sensor	640x480 (307 Kpixels)	80	500 dpi
DB2_B	Optical Sensor	328x364 (119 Kpixels)	80	500 dpi
DB3_B	Thermal sweeping Sensor	300x480 (144 Kpixels)	80	512 dpi
DB4_B	SFinGe v3.0	288x384 (108 Kpixels)	80	about 500 dpi

Detailed characteristics of the databases are summarized in Table 1. We use Matlab 2014a to perform the experiment.

4.2. Evaluation

This study evaluates two schemes performance. There are the performance of descriptor clustering and fingerprint classification. For descriptor clustering, we use Residual Sum of Square (RSS) as the internal criterion evaluation method. For the classification problem, the performance is measured by using accuracy defined as the number of correctly classified fingerprint divided by the test number. RSS is calculated as follows:

$$RSS = \sum_{k=1}^{K} RSS_k \tag{1}$$

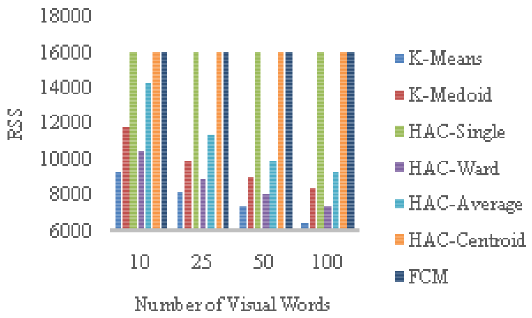
$$RSS_k = \sum_{i=1, x \in c}^{m} \sum_{j=1}^{n} \left(x_{ij} - c_{kj} \right)^2 \tag{2}$$

Where K is the number of cluster, x is the keypoint, c is the centroid of a cluster, m is the number of keypoint in a cluster and n is the vector length of a keypoint. The lower RSS value means the better cluster quality.

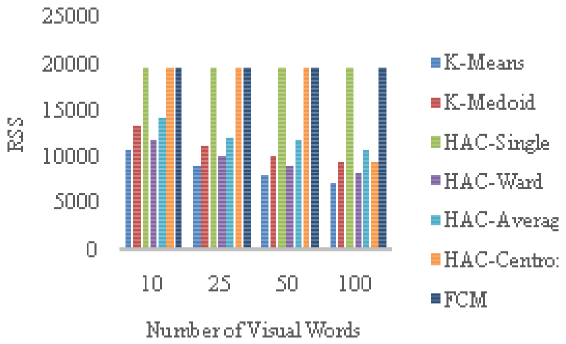
Our experiment perform 10-fold cross validation for the classification. Fold cross validation is a technique to separates the dataset randomly into training and testing dataset. This technique will divides the dataset into 10 portions. In this case, each portion contains 8 fingerprint images. Nine portion were used in training process and the last portion were used in testing process. The 10-fold cross validation runs the 10 portion in 10 times.

4.3. Performance Evaluation of Descriptor Clustering

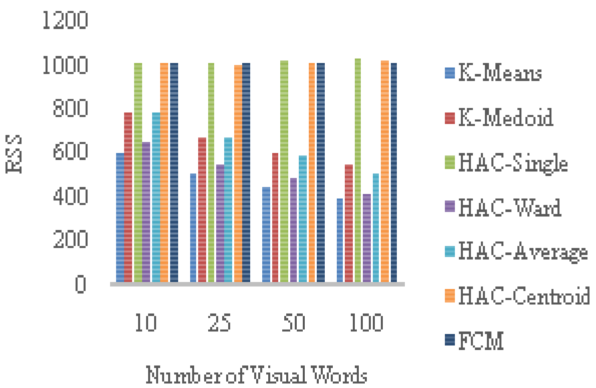
We compare four famous partition clustering algorithm: *k*-means, *k*-medoid, hierarchical agglomerative and fuzzy c-means for descriptor clustering. We can see in Figure 3 and 4. Based on the figures, the smallest *RSS* is achieved by *k*-means, followed by HAC-ward, *k*-medoid, and HAC-average. *RSS* decreases significantly when many number of vocabulary were implemented.



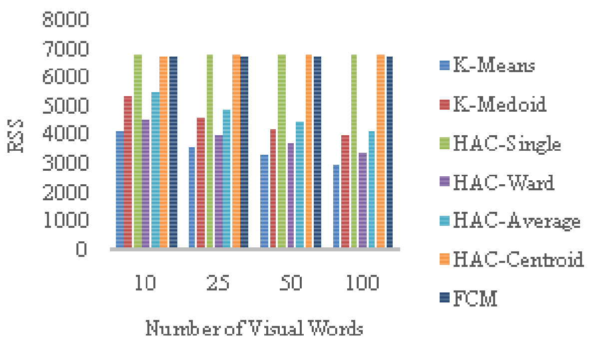
a) DB1_B.



b) DB2_B.

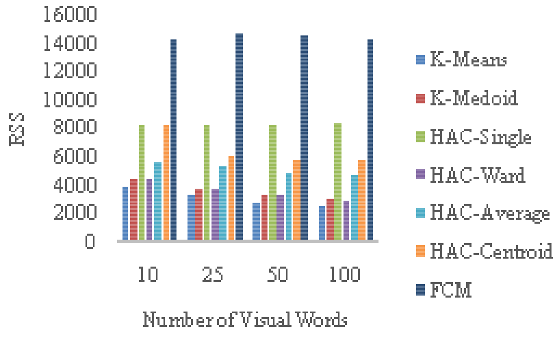


c) DB3_B.

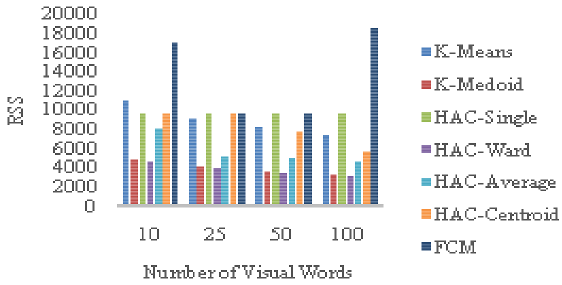


d) DB4_B.

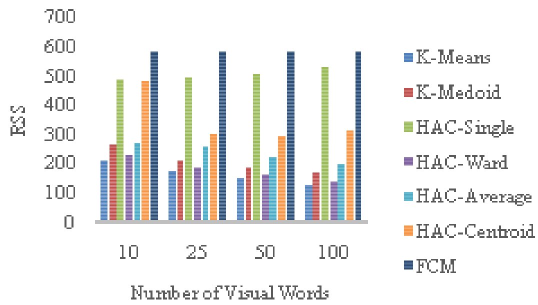
Figure 3. Homogeneity of different clustering with SURF-128 descriptor from FVC2004.



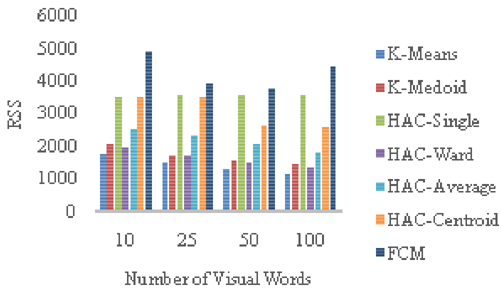
a) DB1_B.



b) DB2_B.



c) DB3_B.



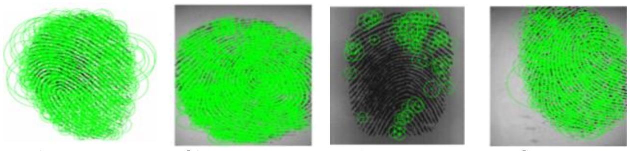
d) DB4_B.

Figure 4. Homogeneity of different clustering with SURF-64 descriptor from FVC2004 databases.

The worst algorithms are HAC-single, HAC-centroid and FCM. These three algorithms did not reduce *RSS* significantly although many number of vocabularies were implemented. This comparison has been evaluated in different databases and different the length vector of SURF.

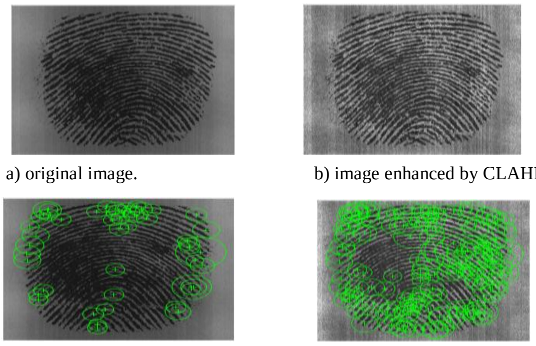
4.4. Performance Evaluation of Fingerprint Classification

In this subsection, we evaluate the performance of fingerprint classification. We adopt *k*-means to cluster the descriptors, since it produces smaller *RSS* compared to others. Our fingerprint classification also implemented CLAHE to enhance the quality of images. We can see in Figure 5, DB3 is more darkness than the other fingerprint databases in FVC2004. This effectiveness is shown in Figure 6. CLAHE is effective to improve the number of descriptors. Figure 7 and 8 show the different histogram between original fingerprint image and enhanced fingerprint image.



a) DB1_B. b) DB2_B. c) DB3_B. d) DB4_B.

Figure 5. Example of fingerprint and their keypoints descriptor from FVC2004 databases.



a) original image. b) image enhanced by CLAHE.

c) SURF-64 descriptor of original image. d) SURF-64 descriptor of enhanced.

Figure 6. Example of fingerprint image and their keypoints descriptor from DB3_B FVC2004 databases.

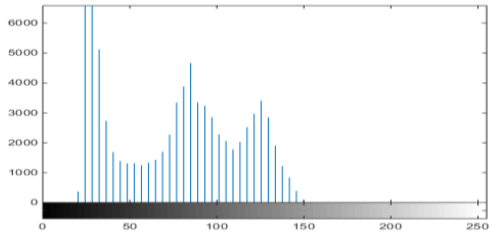


Figure 7. Histogram of original fingerprint image.

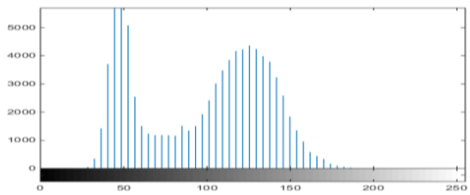


Figure 8. Histogram of enhanced fingerprint image by using CLAHE.

Before we evaluate the using of CLAHE, we test several values of clip limit in different distribution methods. Figure 9 seems that the performance of classification is still low in different clip limit. Figure 10 seems better. This is because the performance achieves optimal accuracy of more than 90% by using exponential distribution and clip limit 0.001.

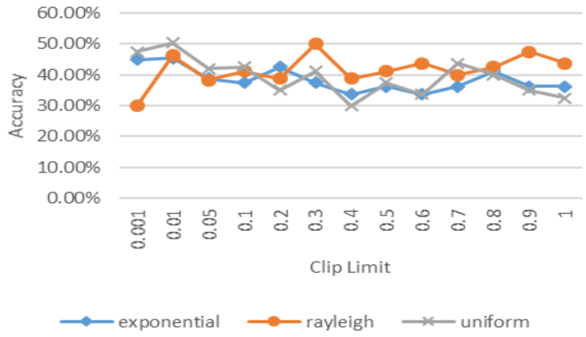


Figure 9. Clip limit evaluation for fingerprint dataset (DB3_B, SURF-64, 10 visual word).

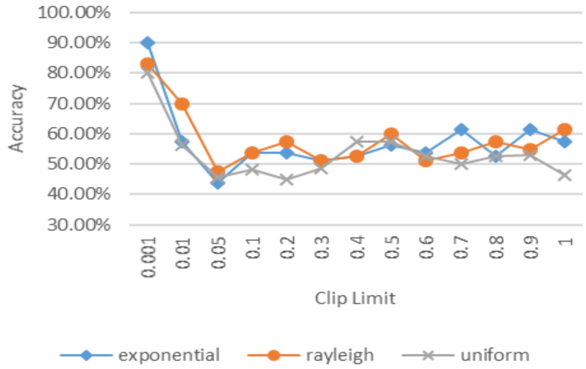


Figure 10. Clip limit evaluation for fingerprint dataset (DB4_B SURF-64, 10 visual word).

Because of this reason, we implement exponential distribution and clip limit 0.001 to evaluate the using of CLAHE in BOVW based fingerprint classification. Figure 11 and Figure 12 show that CLAHE enables to improve the performance of fingerprint classification. In each database, the performance of CLAHE performs well compares to fingerprint classification without CLAHE. In our work, the performance of SURF-64 outperforms SURF-128 in term of accuracy.

SURF-64 and SURF-128 have the same number of descriptors, the different is in the length of the descriptor. In Table 2 and 3, we compare the number of descriptors between SURF without CLAHE and SURF with CLAHE. In these tables show that CLAHE increases the number of descriptor in FVC2004 databases.

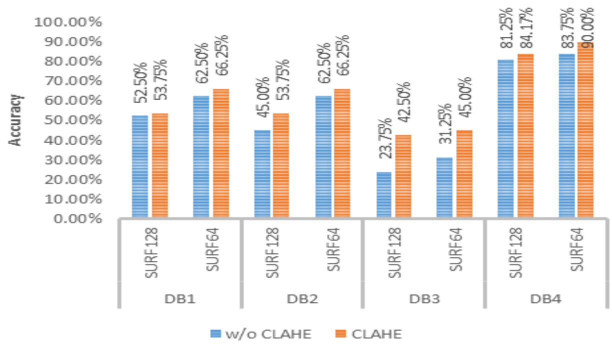


Figure 11. Accuracy of classification using *k*-means as descriptor clustering (10 visual word, exponential distribution of CLAHE, clip limit 0.001).

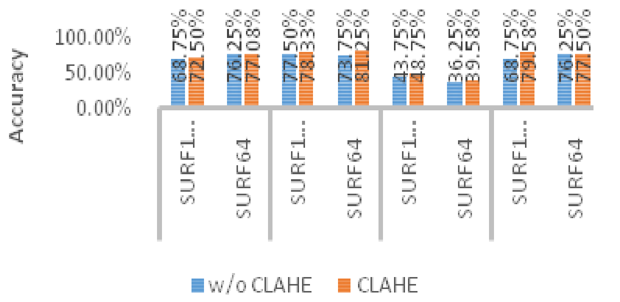


Figure 12. Accuracy of classification using *k*-means as descriptor clustering (10 visual word, exponential distribution of CLAHE, clip limit 0.001).

Table 2. The number of descriptor in each database.

	DB1_B	DB2_B	DB3_B	DB4_B
without CLAHE	46203	54903	3305	23937
with CLAHE	63679	104546	51920	59611

Table 3. Average number of descriptor in each database.

	DB1_B	DB2_B	DB3_B	DB4_B
without CLAHE	577.54	686.29	41.31	299.21
with CLAHE	795.99	1306.83	649.00	745.14

Figure 13 shows the execution time of SURF in different databases. The speed is measured on Intel i7 8GHz. We observe that SURF needs more time to extract the descriptors in the DB2. It happens since there are many descriptors extracted from DB2. On the contrary, DB3 has the fastest execution time, since DB3 has the smaller number of descriptors than the other databases. This is quite reasonable, since the low quality of DB3 fingerprint images.

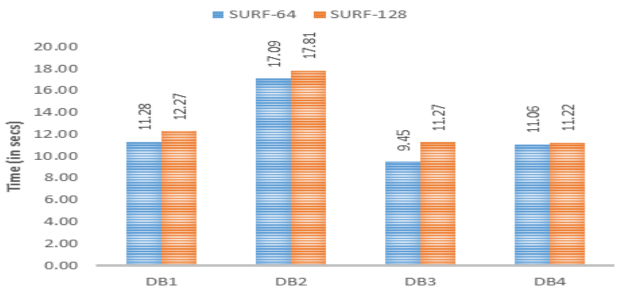


Figure 13. Execution times of descriptor extraction in different databases.

5. Conclusions

This paper presents a fingerprint classification model based on BoVW. The proposed model consists of fingerprint image enhancement, descriptor extraction, descriptor clustering, BoVW construction and classification. There are two evaluations of this study, which are the performance of clustering algorithm for grouping the descriptors and the performance of classification. Our comparison show that *k*-means outperform than the other clustering algorithm in term of the homogeneity of the cluster. For the classification performance, CLAHE is able to achieve a better accuracy of classification in four fingerprint databases FVC2004.

References

[1] Ahmad F. and Mohamad D., "A Review on Fingerprint Classification Techniques," *International Conference on Computer Technology and Development*, Kota Kinabalu, pp. 411-415, 2009.

[2] Balti A., Sayadi M., and Fnaiech F., "Fingerprint Verification Based on Back Propagation Neural Network," *Journal of Control Engineering and Applied Informatic*, vol. 15, no. 3, pp. 53-60, 2013.

[3] Ding G., Wang J., and Qin K., "A Visual Word Weighting Scheme Based on Emerging Itemsets for Video Annotation," *Information Processing Letters*, vol. 110, no. 16, pp. 692-696, 2010.

[4] Do T., Lenca P., and Lallich S., "Classifying Many-Class High-Dimensional Fingerprint Datasets Using Random Forest of Oblique Decision Trees," *Vietnam Journal of Computer Science*, vol. 2, no. 1, pp. 3-12, 2015.

[5] Gago-Alonso A., Hernández-Palancar J., Rodríguez-Reina E., and Muñoz-Briseño A., "Indexing and Retrieving in Fingerprint Databases Under Structural Distortions," *Expert Systems with Applications*, vol. 40, no. 8, pp. 2858-2871, 2013.

[6] Girgis M., Sewisy A., and Mansour R., "Robust Method for Partial Deformed Fingerprints Verification Using Genetic Algorithm," *Expert Systems with Applications*, vol. 36, no. 2, pp. 2008-2016, 2009.

[7] He S., Zhang C., and Hao P., "Clustering-Based Descriptors for Fingerprint Indexing and Fast Retrieval," *in Proceedings of the 9th Asian Conference on Computer Vision*, pp. 354-363, Queenston, 2010.

[8] Jayaraman U., Prakash S., and Gupta P., "An Efficient Color and Texture Based Iris Image Retrieval Technique," *Expert Systems with Applications*, vol. 39, no. 5, pp. 4915-4926, 2012.

[9] Li Z. and Feng X., "Near Duplicate Image Detecting Algorithm Based on Bag of Visual Word Model," *Journal of Multimedia*, vol. 8, no. 5, pp. 557-564, 2013.

[10] Macqueen J., "Some Methods of Classification and Analysis of Multivariate Observations," *in Proceedings of the 5th Berkeley Symposium on Mathematical Statistics and Probability*, Berkeley, pp. 281-297, 1967.

[11] Maio D., Maltoni D., Cappelli R., Wayman J., and Jain A., "FVC2004: Third Fingerprint Verification Competition," *in Proceedings of 1st International Conference on Biometric Authentication*, Hong Kong, pp. 1-7, 2004.

[12] Maltoni D., Miao D., Jain A., and Prabhakar S., *Handbook of Fingerprint Recognition*, Springer, 2003.

[13] Mikolajczyk K. and Schmid C., "A performance Evaluation of Local Descriptors," *IEEE Transactions On Pattern Analysis and Machine Intelligence*, vol. 27, no.10, pp. 1615-1630, 2005.

[14] Motwakel A. and Shaout A., "Fingerprint Image Quality Fuzzy System," *The International Arab Journal of Information Technology*, vol. 13, no. 1A, pp. 171-177, 2016.

[15] Munir M., Javed M., and Khan S., "A Hierarchical K-means Clustering Based Fingerprint Quality Classification," *Neurocomputing*, vol. 85, pp. 62-67, 2012.

[16] Nanni L. and Lumini A., "Descriptors for Image-Based Fingerprint Matchers," *Expert Systems with Applications*, vol. 36, no. 10, pp. 12414-12422, 2009.

[17] Reza A., "Realization of the Contrast Limited Adaptive Histogram Equalization (CLAHE) for Real-Time Image Enhancement," *Journal of VLSI Signal Processing Systems for Signal, Image and Video Technology*, vol. 38, no. 1, pp. 35-44, 2004.

[18] Sepasian M., Balachandran W., and Mares C., "Image Enhancement for Fingerprint Minutiae-Based Algorithms Using CLAHE, Standard Deviation Analysis and Sliding Neighborhood," *Proceedings of the World Congress on Engineering and Computer Science*, San Francisco, 2008.

[19] Sepasian M., Mares C., Azimi S., and Balachandran W., "Image Enhancement for Minutiae-Based Fingerprint Identification," *in Proceedings of 37th IEEE Applied Imagery Pattern Recognition Workshop*, Washington DC, pp. 1-4, 2008.

[20] Shuai X., Zhang C., and Hao P., "Fingerprint Indexing Based on Composite Set of Reduced SIFT Features," *in Proceedings of the International Conference on Pattern Recognition*, Tampa, pp. 1-4, 2008.

[21] Sivic J. and Zisserman A., "Video Google: A text Retrieval Approach to Object Matching in Videos," *in Proceedings of the International Conference on Computer Vision*, Nice, pp. 1470-1477, 2003.

[22] Tiwari K., and Gupta P., "An Efficient Technique for Automatic Segmentation of Fingerprint ROI from Digital Slap Image," *Neurocomputing*, vol. 151, no.3, pp. 1163-1170, 2015.

[23] Yang J., Jiang Y., Hauptmann A., and Ngo C., "EvaluatingBag-of-Visual-Words Representations in Scene Classification," *in Proceedings of the International Workshop on Workshop on Multimedia Information Retrieval*, Texas, pp. 197-206, 2007.

[24] Zhang J., Liu X., Zhuo L., and Wang C., "Social Images Tag Ranking Based on Visual Words in Compressed Domain," *Neurocomputing*, vol. 153, pp. 278-285, 2015.

[25] Zhang J., Sui L., Zhuo L., Li Z., and Yang, Y., "An Approach of Bag-of-Words Based on Visual Attention Model for Pornographic Images Recognition in Compressed Domain," *Neurocomputing*, vol. 110, pp. 145-152, 2013.

Pulung Andono is a lecturer in Faculty of Computer Science, University of Dian Nuswantoro, Semarang, Indonesia. He received his doctoral degree from Institut Teknologi Sepuluh Nopember (ITS), Surabaya, Indonesia. His research interests are computer vision, machine learning, soft computing and intelligent system.

Catur Supriyanto is a lecturer in Faculty of Computer Science, University of Dian Nuswantoro, Semarang, Indonesia. He received his master degree from Universiti Teknikal Malaysia Melaka (UTeM), Malaysia. His research interests are information retrieval, machine learning, soft computing and intelligent system.