Digital image processing: Offline handwritten signature identification using local binary pattern and rotational invariance local binary pattern with learning vector quantization

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Abstract. The Handwritten signature is one of the authentication tools that humans have to determine the authenticity of a file or document. The difference between offline and online handwritten signatures is that offline signatures requires a scanner while online signatures use a stylus. The feature extraction methods used are Local Binary Pattern (LBP), uniform LBP, LBP 8 rotation, and uniform LBP 8 rotation. Learning algorithm used is Learning Vector Quantization (LVQ). This study used 200 images data, derived from 20 participants handwritten signature with contribution of 10 signatures each participants. Training data and test data will be divided based on the k-fold cross validation classification then tested based on 4 groups of data sets with certain parameters. Data set 1 consisted of 5 participants, data set 2 consisted of 10 participants, data set 3 consisted of 15 participants, and data set 4 consisted of 20 participants. The best system performance results with the highest accuracy are in training and testing of data set 1 with maximum of 100 iteration for each method. The results of system accuracy is very affected by total number of participants used, which is the more the number of participants with signatures processed, the accuracy will be reduced. The detailed results of system performances accuracy using data set 1 for the LBP extraction method obtained an accuracy of 84%, uniform LBP obtained an accuracy of 90%, LBP 8 rotation obtained an accuracy of 86%, and LBP 8 uniform rotation obtained an accuracy of 80%.

1. Introduction

The authenticity of a file or document usually requires a sign of validation or authentication from the source of the file. One of the authentication tools used is a signature. As important as the meaning of a signature is, legally it is also stated that the function of a signature is to characterize or individualize a deed [1].

Based on the process, signatures are divided into two types, which is offline and online. At the image processing stage, the signature image has several distinctive features that can be used as parameters to be processed, some are patterns and textures that tend to be different from each person when writing a signature. Local Binary Pattern (LBP) is a simple and efficient feature extraction
method for texture identification, where each pixel in an image is represented by the surrounding pixels and makes the calculation result a binary value [2].

The LBP method itself produces 256 numbers of features, which are quite a lot. Therefore, a uniform LBP method was developed which produced 59, fewer features than LBP [3]. To deal with the feature extraction in rotational images problem, LBP development methods such as rotational invariance LBP and uniform rotational invariance LBP are used [4]. The LBP rotation invariance used is the 8 rotation LBP which will be discussed in this study (0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°), the average value of the total histogram is obtained from each angle. The concept of LBP rotation is the same as LBP 8 uniform rotation.

One of the classification methods in ANN is Learning Vector Quantization (LVQ). This method is a method of classifying patterns, where each unit to the output represents a particular class or category [4]. Song (1997) in a study comparing five neural network models, stated that LVQ has a faster learning speed, lower error rates, better resistance to system and environmental variations, and requires less training data compared to other supervised learning which is more. complex such as backpropagation [5]. Learning Vector Quantization can be collaborated with the LBP and Rotational Invariance LBP methods so that it can identify offline signature images.

2. Methods

2.1. Digital image processing

Image Processing is a form of signal processing, where the input is in form of an image, such as a photo or video, and the output of the image processing is in the form of characteristics or parameters related to the image. The output of image processing does not have to be an image, but can be part of the image.

2.2. Preprocessing

Preprocessing is a data processing process (in this case a digital image) so that the data can be used for the next stage. The goal is to create a digital image to suit its feature extraction needs. Some of the preprocessing used in this research are image acquisition, grayscaling, segmentation, area filtering and object bounding areas. This image is obtained by eliminating a number of RGB image information into a grayscale image shown in the equation [6]:

\[ g(x,y) = (0.299 * R) + (0.587 * G) + (0.114 * B) \]  

(2.1)

Segmentation is a process to convert an image into a binary image which has 2 values (0 for black and 1 for white). This process also has been useful to remove noise from the image.

\[ T(x,y) = \begin{cases} 0, & g(x,y) \geq \text{threshol value} \\ 1, & g(x,y) < \text{threshol value} \end{cases} \]  

(2.2)

Area filtering is useful for removing these small parts by giving a threshold value which represents the minimum area of the combined pixels that are connected to each other, so that the combined area with an area below the specified threshold will be excluded from the image. One of the algorithms is Flood Fill Pixel Reduction (FFPR). The FFPR algorithm can be stated as follows:

a. Initialization: The color of the object is assumed to be white, the variable \( h = 0 \), create array 2 dimension for variable signs = 0 and check = "false",

b. For \( x = 1 \) to the image width, \( y = 1 \) to the image height, perform steps c to e,

c. If pixels (x, y) are white and check (x, y) = false then perform an 8 direction flood fill algorithm,

d. For each direction in the flood fill algorithm, enter an h variable and add it with 1,
e. The flood fill algorithm stops when the array of signs and checks obtain with all the coordinates of each pixel traversed by the flood fill algorithm is $h$ and is true, if it is not fulfilled continue to step c.

f. Any pixel that has an array of signs less than the threshold value will turn black.

2.3. Local Binary Pattern (LBP)
This approach was introduced by Ojala et al. in 1996 [7]. LBP uses eight pixels in a 3 x 3 pixel block, the basic formula of this operator places no restrictions on the size of the neighbors or on the number of sampling points/neighbors. To determine the coordinates of the neighboring pixels $(x_i, y_i)$ can be determined by the following equation [8]:

\[
x_i = x_c + R \cos \left( \frac{2\pi i}{p} \right)
\]
\[
y_i = y_c + R \sin \left( \frac{2\pi i}{p} \right)
\]

If the gray value of the central pixel is $g_c$ and the value of its neighbor is $g_i$ with $i = 0, \ldots, P-1$, then the LBP value for pixels $(x_c, y_c)$ can be found using equation:

\[
LBP_p,8(x_c, y_c) = \sum_{i=0}^{P-1} s(g_i - g_c)2^i
\]

2.3.1. Uniform Local Binary Pattern (uniform LBP). Ojala et al. (2002) made observations and found that certain LBP patterns have important information about a texture. Patterns that have this important information are called uniform patterns. LBP is said to be uniform if the discontinuities or bit transitions of 0/1 are at most two. For example 00000000 (0 transitions), 11001111 (2 transitions), and 11001111 (2) are uniform patterns, while 11001001 (4 transitions) and 10101001 (6 transitions) are not uniform patterns [9]. Mathematically, uniform patterns can be expressed as follows.

\[
LBP_{u,2}^p(x_c, y_c) = |s(g_{p-1} - g_c) - s(g_0 - g_c)| + \sum_{i=0}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)|
\]

2.3.2. 8 Rotation Local Binary Pattern (8 Rotation LBP). 8 rotation LBP is a development of the LBP algorithm where each LBP block pattern is rotated into 8 corner directions (0°, 45°, 90°, 135°, 180°, 225°, 270°, 315°). These eight LBPs are also calculated by Equation (2.5), of course, with the initial position $g_0$ which varies depending on the direction of the angle. LBP 8 rotation is often symbolized with $LBP_{\theta,R}(x_c, y_c)$, where $\theta$ represents the angle while LBP 8 rotations using a uniform pattern is symbolized with $LBP_{\theta,R}^{u,2}$.

2.4. Artificial neural network
Artificial Neural Network (ANN) is an information processing system that has a relationship with biological neural networks [10]. The knowledge that is in the artificial neural network is not programmed to produce a certain output, but based on the information it receives. All outputs or stories taken by the network are based on their experiences during the learning process. In the learning process, input and output patterns are inserted into the neural network and the network will be taught to provide acceptable answer [11]. One way to initialize weights is to initialize them according to the average input data. This method is a common process were being used to initialize weights in the LVQ architecture.

2.4.1. Normalization. Normalization or scaling is the procedure of changing data so that it is on a certain scale. This scale can be between (0,1), (-1,1) or any other scale you want according to upper boundary (UB) and lower boundary (LB). The normalization process is carried out on the data
obtained through the feature extraction results in this study. To change the data \((x)\) to a new scale \((X')\) for each data can be done with equations:

\[
X' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times (UB - LB) + LB \tag{2.7}
\]

2.4.2. **Learning Vector Quantization (LVQ).** Learning Vector Quantization (LVQ) is a pattern classification method where each unit of output represents a particular class or category [12]. The LVQ network architecture consists of an input layer and an output layer. The input layer is connected to the output layer by weight. The steps of the LVQ algorithm are as follows:

a. Initialization: weight \((w)\), epoch maximum \((max\ epoch)\), the expected learning rate minimum \((eps \alpha)\), learning rate \((\alpha)\).

b. Add: input data \(x(n,m); m = \) input amount, \(n = \) data amount, target \(T(1,n)\).

c. Set initial condition: \(epoch = 0\).

d. Do if: \((epoch < max\ epoch)\) or \((\alpha \leq eps \alpha)\)
   
   d.1. \(epoch = epoch + 1;\)
   
   d.2. Do for \(i = 1 \) to \(n\)
   
   d.2.1. Determine \(j\) such that, until the minimum using the following formula.

\[
C_j = \| x - w_j \| \tag{2.8}
\]

   d.2.2. Update \(w_j\) with condition:

   If \(T = C_j\) Then:

\[
w_j^{(new)} = w_j^{(old)} + \alpha (x - w_j^{(old)}) \tag{2.9}
\]

   If \(T \neq C_j\) Then:

\[
w_j^{(new)} = w_j^{(old)} - \alpha (x - w_j^{(old)}) \tag{2.10}
\]

   d.3. Reduce the learning rate \((\alpha)\) using the following formula:

\[
\alpha^{(new)} = \alpha^{(old)} - (0,1*\alpha^{(old)}) \tag{2.11}
\]

3. **Results and discussion**

The test results are divided into 2 parts, such as testing the digital image processing parameters and testing the parameters of the Learning Vector Quantization neural network.

3.1. **Digital image processing parameters test**

The parameters to be tested in this system include the segmentation threshold value and the areas filtering threshold value.

3.1.1. **Segmentation threshold value.** The tested value starts from the middle value of 128 to the highest value of the spectrum 255. Therefore, the threshold value is enlarged to approach the highest grayscale intensity spectrum value until a threshold value of 210 is obtained. Based on this threshold value, the results of the observed object are able to describe a good signature pattern, and clearly, for all image data used in this research. Randomized threshold value trials on several signature images can be seen in Table 1.
Table 1. The results of the randomized threshold value experiment on several images.

| Name | Image of an acquired signature | Threshold value = 128 | Threshold value = 160 | Threshold value = 210 |
|------|--------------------------------|----------------------|----------------------|----------------------|
| Alyan | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) |
| Budi | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |

3.1.2. Areas filtering threshold value. The values used are natural numbers (N = 1,2,3,4,5, ...). A value is selected if the results of ordinary observations of objects resulting from system processing show a clear pattern without any residual noise. Because each participant has a different threshold value. Therefore, to obtain 1 threshold value used by the system for all image data, the average threshold value of all participants was taken. The average value is 3.1 which is then rounded to 3.

3.2. Parameters of the learning vector quantization neural network test

3.2.1. Testing parameters. The results of training and network testing conducted 10 times according to the number of folds. The best results from each parameter combination are combined to compare the accuracy of the system. The LBP extraction obtained the highest system accuracy results of 68.50% and the lowest 55%. The uniform LBP extraction obtained the highest system accuracy results of 66.50% and the lowest 55%. The 8 rotation LBP has the highest system accuracy results of 70.50% and the lowest is 52%. The uniform 8 rotation LBP obtained the highest system accuracy results of 66.50% and the lowest 44.50%.

3.2.2. Testing training data and test data. This testing phase displays the various results of calculating the accuracy of the training data and test data formed through k-fold cross validation (see table 2-5).

Table 2. Results of data set 1 training (50 data) with the highest system accuracy.

| Fold | Feature name | Learning Parameters | Accuracy (%) | Training Time (mm:ss:ms) |
|------|--------------|---------------------|--------------|-------------------------|
|      |              | Init. Learning rate (α) | Max Epoch | Learning Rate min. to stop (eps α) | Epoch | Training Data | Testing Data | System |        |
| 4    | LBP          | 0.01                | 100        | 0.01                    | 1     | 82.22%       | 100.00%      | 84.00% | 00:00:00:009 |
| 5    | Uniform LBP  | 0.1                 | 100        | 0.1                     | 1     | 88.89%       | 100.00%      | 90.00% | 00:00:00:002 |
| 8    | 8 Rotation LBP | 0.1                | 100        | 0.1                     | 1     | 86.67%       | 80.00%       | 86.00% | 00:00:00:009 |
| 5    | Uniform 8 Rotation LBP | 0.1              | 100        | 0.01                    | 22    | 77.78%       | 100.00%      | 80.00% | 00:00:00:114 |
### Table 3. Results of data set 2 training (100 data) with the highest system accuracy.

| Fold | Feature name  | Learning Parameters | Accuracy (%) | Training Time (mm:ss:ms) |
|------|---------------|---------------------|--------------|--------------------------|
| 9    | LBP           | 0.01 100 0.001 22   | 73.33%       | 00:00:00:788             |
| 9    | Uniform LBP   | 0.01 100 0.0001 44  | 72.22%       | 00:00:00:568             |
| 5    | 8 Rotation LBP| 0.1 100 0.001 44   | 71.11%       | 00:00:01:620             |
| 7    | Uniform 8 Rotation LBP | 0.01 100 0.0001 44  | 66.67%       | 00:00:00:737             |

### Table 4. Results of data set 3 training (150 data) with the highest system accuracy.

| Fold | Feature name  | Learning Parameters | Accuracy (%) | Training Time (mm:ss:ms) |
|------|---------------|---------------------|--------------|--------------------------|
| 9    | LBP           | 0.01 100 0.001 22   | 68.89%       | 00:00:01:710             |
| 1    | Uniform LBP   | 0.1 100 0.001 44   | 71.11%       | 00:00:01:568             |
| 9    | 8 Rotation LBP| 0.01 100 0.0001 44  | 70.37%       | 00:00:03:377             |
| 1    | Uniform 8 Rotation LBP | 0.1 100 0.01 22   | 67.41%       | 00:00:00:561             |

### Table 5. Results of training data set 4 (200 data) with the highest system accuracy.

| Fold | Feature name  | Learning Parameters | Accuracy (%) | Training Time (mm:ss:ms) |
|------|---------------|---------------------|--------------|--------------------------|
| 6    | LBP           | 0.01 100 0.001 22   | 66.11%       | 00:00:02:859             |
| 6    | Uniform LBP   | 0.01 100 0.0001 44  | 65%          | 00:00:01:853             |
| 1    | 8 Rotation LBP| 0.1 100 0.0001 66  | 72.22%       | 00:00:10:371             |
| 7    | Uniform 8 Rotation LBP | 0.01 100 0.0001 44  | 64.44%       | 00:00:01:837             |

### 4. Conclusion

The results found through experiments on each extraction method with a certain combination of parameters are data set 1 with 50 image data having the highest accuracy (LBP: 84%; uniform LBP: 90%; 8 rotations LBP: 86%; uniform 8 rotations LBP: 80%) compared to other data sets which shows lower accuracy results. Through this experiment it can be proven that there is an influence on the number of participants on the accuracy of the system, in other words the more participant data used, the lower the accuracy of the resulting system, and vice versa.

### Reference

[1] Widodo A W and Harjoko A 2015 Sistem Verifikasi Tanda Tangan Off-Line Berdasar Ciri Histogram of Oriented Gradient (HOG) dan Histogram of Curvature (HoC) 2(1) p 1 VIII

[2] Pietikäinen M 2010 Local Binary Patterns Scholarpedia 5(3) p 9775
[3] Mehta R and Egiazarian K 2013 Rotated Local Binary Pattern (RLBP): Rotation invariant texture descriptor 2nd International Conference on Pattern Recognition Applications and Methods, ICPRAM 2013, Barcelona, Spain, 15.-18.2.2013. Barcelona, Spain: Institute of Electrical and Electronics Engineers IEEE pp 497-502

[4] Nova D and Estévez P A 2014 A review of learning vector quantization classifiers," Neural Computing and Applications 25 pp 511-524

[5] Song Y N, Xuan Q Y, and Johns A T 1996 Comparison studies of five neural network based fault classifiers for complex transmission lines Proceedings of 1996 Canadian Conference on Electrical and Computer Engineering 2 pp 745-749

[6] Gonzalez R C, Woods R E, and Eddins S L 2004 Digital Image Processing, 3rd ed. (New Jersey, United States of America: Pearson Prentice Hall)

[7] Mäenpää T 2003 The local binary pattern approach to texture analysis — extensions and applications Doctoral Dissertation (187

[8] Ahonen T, Matas J, He C, and Pietikäinen M 2009 Rotation Invariant Image Description with Local Binary Pattern Histogram Fourier Features Image Analysis. (Heidelberg, Berlin: Springer) 5575

[9] Ojala T, Pietikäinen M, and Maenpaa T 2002 Multiresolution gray-scale and rotation invariant texture classification with local binary patterns IEEE Transactions on Pattern Analysis and Machine Intelligence 24(7) pp 971-987

[10] Fausett L L 1994 Fundamentals of neural networks: architectures, algorithms, and applications (Englewood, Cliffs, United States of America: Prentice Hall)

[11] Puspitaningrum D 2006 Pengantar Jaringan Syaraf Tiruan (Yogyakarta: Andi Publisher)

[12] Kohonen T 1989 Self-Organization and Associative Memory (Heidelberg, Berlin: Springer)