ESTIMATION OF FINGERPRINT ORIENTATION FIELD BY UTILIZING PRIOR KNOWLEDGE AND SELF-ORGANIZING MAP

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ABSTRACT

This study proposes a new method of estimating fingerprint orientation field by utilizing prior knowledge of fingerprint images and Self-Organizing Map (SOM). The method is based on the assumption that fingerprint images have some common properties that can be systematized to build prior knowledge. In this method, each fingerprint image was divided into 16 regions equally and the regions were analyzed separately. To analyze the regions, they were divided into blocks of 8x8 pixels. Feature vector of each block was constructed by summing the pixel intensity values in row and column wise. Furthermore, feature vectors of the blocks were concatenated to form a feature matrix of the region. The matrix was then processed by SOM to find the most dominant orientation field of the region. The experiment results showed that the chosen feature gave short epochs of SOM training. In addition, the method was able to estimate the orientation field of most regions. However, the method could not precisely determine the orientation field if the blocks are dominated by background pixels.

1. INTRODUCTION

Fingerprint image is mostly composed of parallel ridges that form a pattern. It is accepted that ridge pattern in a fingerprint is unique and will not change in the entire life of the owner. In some locations of fingerprint images, a ridge forms a straight line, whereas in other locations it forms an arch or a curve. In other words, the direction or the orientation of a ridge corresponds to its location. A term commonly used to quantify the direction or the orientation of ridges is orientation field.

Some literature defines fingerprint orientation field as the local orientation of the ridges-valley structure (Chen, 2012; Tao *et al.*, 2010) or the ridge-valley flow orientation at each location (Wang and Hu, 2011). Hence, each point in the fingerprint image, even that is not located in ridge-line, has its own orientation field. It is common to specify the orientation field in block-wise rather than in pixel-wise. For instance, in (Liu and Liu, 2012) the writers assumed that the orientation field is a 2D matrix composed of the orientation of pixels that present the dominant ridge orientations of a block in the fingerprint image.

Orientation field is an important feature in the fingerprint image. It contains useful information that can be used to distinguish fingerprints. Researchers used orientation field in some fingerprint processing such as distinguishing fingerprint images from non-fingerprint images (Yoon and Jain, 2013), separating latent overlapping fingerprints (Feng *et al.*, 2012; Zhao and Jain, 2012), fingerprint indexing (Cappelli, 2011), fingerprint reconstruction (Feng and Jain, 2011), fingerprint identification (Wang and Hu, 2011; Vaidehi and Naresh, 2010), fingerprint matching (Chen *et al.*, 2010), fingerprint

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image enhancement (Yoon *et al*., 2011; Feng *et al*., 2013) and detecting altered fingerprint (Yoon *et al*., 2012). Therefore, it is desirable that methods to estimate the orientation field should be simple, fast and reliable.

This study proposes a new method to estimate fingerprint orientation field based on prior knowledge of fingerprint images. The method works on block-wise basis. We have hypothesized that each ridge has a different orientation in different location or region. Based on this hypothesis, the orientation of blocks represents the orientation of the region where those blocks are located.

The rest of the paper is organized as follows. Section 2 reviews some published orientation field estimation methods, Section 3 describes proposed estimation method, Section 4 presents experiment procedure and results, Section 5 discuss some issues and finally Section 6 presents the conclusion of the paper.

2. RELATED WORKS

The estimation method of fingerprint orientation field is among the most popular topics in fingerprint researches. Various methods have been proposed to estimate the orientation field. In this section, we review some publications related to methods for orientation field estimation, namely gradient-based, model-based and dictionary-based method. In addition, literatures of prior knowledge usage and SOM implementation are reviewed briefly at the end of this section.

Cappelli (2011) used gradient-based method to estimate local ridge-line orientation when he designed fingerprint indexing algorithm. He utilized the orientation field information to estimate ridge-line frequencies as well as to find core position. He reported that the proposed method was fast and accurate. The combination of model-based and gradient-based method was used by (Liu and Liu, 2012) to model the orientation field. Initially, they estimated the local orientation field of a block using common gradient-based method and then transformed it into a complex value. Based on this value, proposed a sparse coding for modelling the real part and the imaginary part separately. They reported that the method was effective to model the orientation field of poor quality fingerprints.

Literature such as (Yoon *et al*., 2011) and (Wang and Hu, 2011) used model-based method to calculate the orientation field. Yoon *et al*. (2011) proposed orientation field estimation method to enhance latent fingerprint. They modeled orientation field into two components of orientation, namely singular orientation and residual orientation. By using this method, they reported that the matching performance of a commercial matcher improved significantly. Wang and Hu (2011) estimated field orientation by using modeling approach when they proposed an identification method to partial fingerprints. They conducted an experiment by analyzing the global topological features. First, they built an inverse orientation model and then solved valid solutions in a general expression for all the inverse models. Finally, they built an algorithm to reconstruct the missing orientation structure. Wang and Hu (2011) reported that this method can improve the performance for partial fingerprint identification. Similarly, (Zhao and Jain, 2012) used a model of the orientation field when they built algorithm for separating overlapping latent fingerprints. Model-based method is commonly used to estimate the orientation field of latent fingerprint due to poor quality and unclear ridge structure of the fingerprint images.

Feng *et al*. (2013) proposed a rather different method to estimate the orientation field of fingerprint. Their method worked on a dictionary that was built based on prior knowledge of the ridge structure in fingerprints. Based on the experiment result, (Feng *et al*., 2013) reported that this method could improve conventional algorithms. Similarly, (Wang and Hu, 2011) utilized prior knowledge when they developed algorithm for estimating the missing parts of fingerprint. They built a prior knowledge by observing the general ridge topology patterns of fingerprints. They reported that the method significantly improve the system performance.

Although these methods showed good performances, however they need some preprocessing and heavy mathematics calculation.

Motivated by the advantages of neural network, some researchers utilize SOM to perform some tasks, such as for classification (Turky and Ahmad, 2010) and for measuring the quality of fingerprint images (Olsen *et al*., 2013). SOM is usually chosen due to its capability to cluster data without supervision. In this method, SOM is used to estimate the orientation field of blocks.

3. PROPOSED METHOD

Although gradient-based, model-based and dictionary-based show satisfied performance, they need long computation due to the need of preprocessing and sometimes postprocessing. In this study, we propose a different method to estimate the orientation field. This method does not need any preprocessing or postprocessing. **Figure 1** is the diagram of the proposed method.
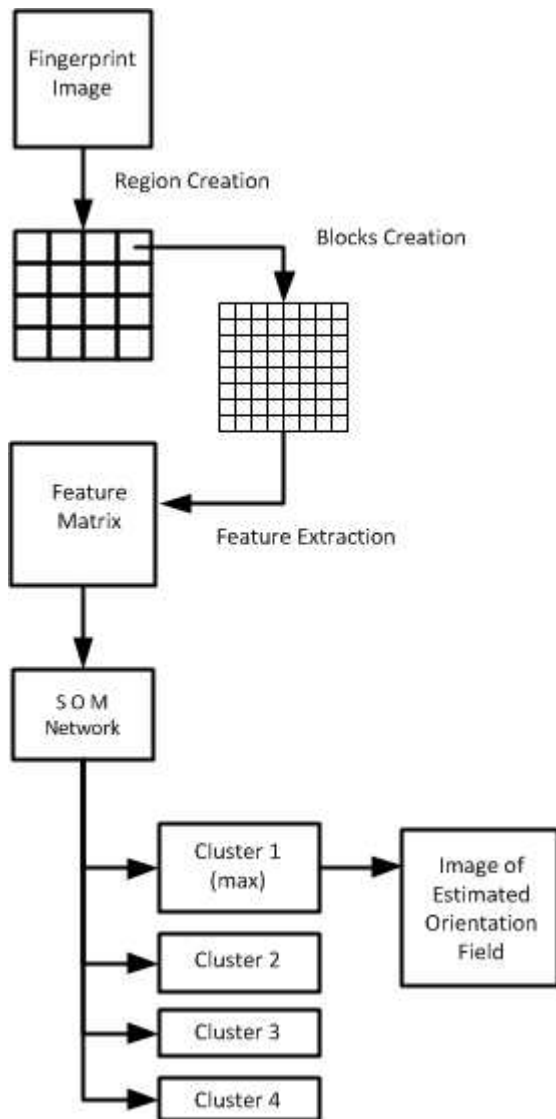
Fig. 1. The diagram of proposed method

The method utilizes prior knowledge of fingerprint images and Self-Organizing map. In this context, prior knowledge is a collection of facts that commonly found in fingerprint images. The prior knowledge can be used to reduce the wrong estimation of ridges' orientation.

Following is some prior knowledge we have observed: (1) It is common that fingerprint images are positioned vertically when examined, (2) most important information of fingerprint images is located in the central area and the bottom part of the image, (3) most ridge orientations in the upper regions is curved inward, (4) some of ridges orientations do not exist in some regions and (5) most regions are dominated by a specific orientation, except regions where cores or bifurcations exist. This prior knowledge was examined in the experiment by using 50 images of all classes of fingerprint, i.e., left-loop, right-loop, whorl, arch and tented-arch. The size of all images is 512×512 pixels.

The method divided each fingerprint image into 16 regions of the same size, so that the size of the regions was 128×128 pixels. The regions were numbered from upper left to the bottom right as shown in **Fig. 2.**

Each region was divided into non overlapping blocks of 8×8 pixels to construct a feature vector of each block. Hence, the number of blocks in a region is 256.

There are some choices of properties or values of blocks which can be extracted to form a feature. The good feature should represent the unique property of the block. In this research, we chose the sum of pixel intensity in the block, vertically and horizontally, to create feature vector. Suppose $I(m, n)$ is the intensity value of a pixel at position (m, n) in a block and then R_m and C_n are calculated by using Equation 1 and 2. To create a feature vector, R_m and C_n are concatenated:

$$R_m = \sum_{n=1}^{8} I(m,n) \qquad m=1,2,...,8 \tag{1}$$

$$C_n = \sum_{m=1}^{8} I(m,n) \qquad n=1,2,...,8 \tag{2}$$

All feature vectors in the region are then arranged to form a feature matrix. This matrix is fed into the SOM network that will classify the blocks into clusters. In our experiment, we limited the number of clusters to four to reduce the possibilities of similar blocks scattered among the clusters. Theoretically, there is no direct mechanism to determine what data grouped in a certain cluster. However, because this method only seeks cluster that have the greatest number of blocks, the index of such cluster can be determined. Then, blocks in that cluster are analyzed separately. In this method, we estimated block's orientation by calculating pixels' gradient in that block using Sobel operator as seen in **Fig. 3**. To calculate the gradient we use Equation 3:

$$\theta = atan\left(\frac{G_y}{G_x}\right) \tag{3}$$

Gx and *Gy* resulted by Sobel operator can be positives or negatives. Because the gradient of ridges ranges from 0° to 180°, we used Equation 4 to calculate the gradient in degrees:

$$\theta = \begin{cases} \operatorname{atan}\left(\dfrac{G_y}{G_x}\right) & \text{if } G_x > 0 \text{ and } G_y > 0 \\[2mm] \operatorname{atan}\left(\dfrac{G_y}{G_x}\right) & \text{if } G_x < 0 \text{ and } G_y < 0 \\[2mm] 90^0 + \left|\operatorname{atan}\left(\dfrac{G_y}{G_x}\right)\right| & \text{if } G_x < 0 \text{ and } G_y > 0 \\[2mm] 90^0 + \left|\operatorname{atan}\left(\dfrac{G_y}{G_x}\right)\right| & \text{if } G_x > 0 \text{ and } G_y < 0 \end{cases} \tag{4}$$

We classified gradient values into eight categories, namely 0°, 22.5°, 45°, 67.5°, 90°, 112.5°, 135° and 157.5°, by using the rules in **Table 1.**
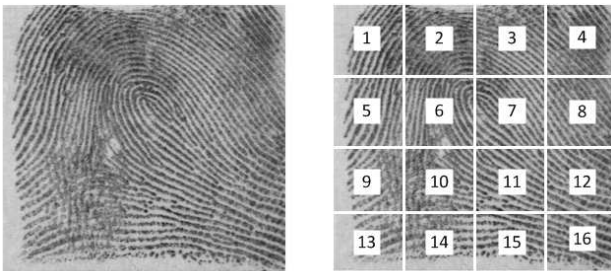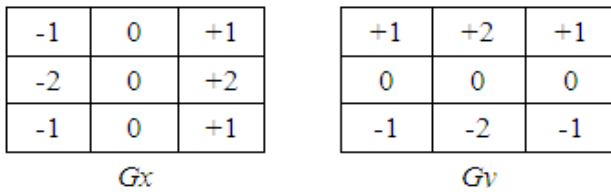
Fig. 2. Fingerprint image and its numbered regions

Fig. 3. Sobel operator

Table 1. Category of gradient

Category	Range of gradient's values
0	$q \leq 0^0$ or $q \geq 168^0$
22.5	$11^0 < q \leq 33^0$
450	$33^0 < q \leq 56^0$
67.5	$56^0 < q \leq 78^0$
900	$78^0 < q \leq 101^0$
112.5	$101^0 < q \leq 123^0$
1350	$123^0 < q \leq 146^0$
157.5	$146^0 < q \leq 168^0$

The most frequent occurrences of pixel's gradient in a block represent the orientation of that block. Furthermore, the most frequent occurrences of block's orientation represent the most dominant orientation field of that region.

4. RESULT AND DISCUSSION

The proposed method was tested using selected fingerprint images of NIST-4 database. We selected images of the five main classes, namely left-loop, right-loop, whorl, arch and tented arch. **Figure 4** shows five images of those classes.

Next, we conducted three experiments, (1) finding the optimum epochs of SOM training, (2) building prior knowledge and (3) testing the performance of the method. To find the optimum epochs we tested 10 values, from 100 to 300 with an increment of 25. We also used one big value, 1000, to test the validity of the result. We used 50 images composed of 10 fingerprint images of each class. The same images were used to show the performance of the orientation field estimation.

4.1. Finding the Optimum Epoch

SOM is categorized as an unsupervised training network. It means that we cannot predict in what cluster a certain data will be grouped. Theoretically, when the number of data in each cluster has been steady, then the sample data that has similar properties would be grouped in a cluster.

To find the optimum epoch, we set SOM topology to 'grid' and four clusters. The purpose of this experiment was to find the minimum epochs when the SOM training started to be steady. **Table 2** shows the short version of the result that contains only 5 blocks of 4096 blocks for each fingerprint image. **Figure 5** clarifies the data presentation of **Table 2**.

Based on **Table 2** and **Fig. 5**, it can be concluded that the SOM training started to be steady at epoch 150. When the number of epochs is increased, i.e. up to 1000, there are no significant changes in the number of clusters' members. This small number of epochs show that the feature was chosen appropriately.

4.2. Building Prior Knowledge

The prior knowledge we listed in Section 3 is based on our finding of visual observation. To support the finding, we generated prior knowledge using 50 samples of fingerprint images, 10 images for each class. First, we calculated the gradient of pixels in each block. Then we determined the gradient of blocks by finding the most

dominant gradient of pixels in the block. Finally, we determined the orientation field of regions by discovering the most dominant gradient of blocks in the region. Second column of **Table 3** presents the most dominant orientation field of each region. We chose this information to be the prior knowledge.

4.3. Performance of the Method

In testing the performance of the method, we chose the optimum epoch number 200 that was taken from **Table 2** and **Fig. 5**. Furthermore, we utilized prior knowledge that was listed in **Table 3**. To determine the indexes of dominant blocks, we inspected the cluster that contains the maximum number of blocks. Based on these indexes, the blocks of the original images were marked using 8×8 pixel marks. To show the orientation estimation, we designed 8 marks that represented 8 directions of the ridge, started from 0° to 157.5° with an increment of 22.5°. **Fig. 6** shows the orientation field estimation of each region based on **Fig. 2**.
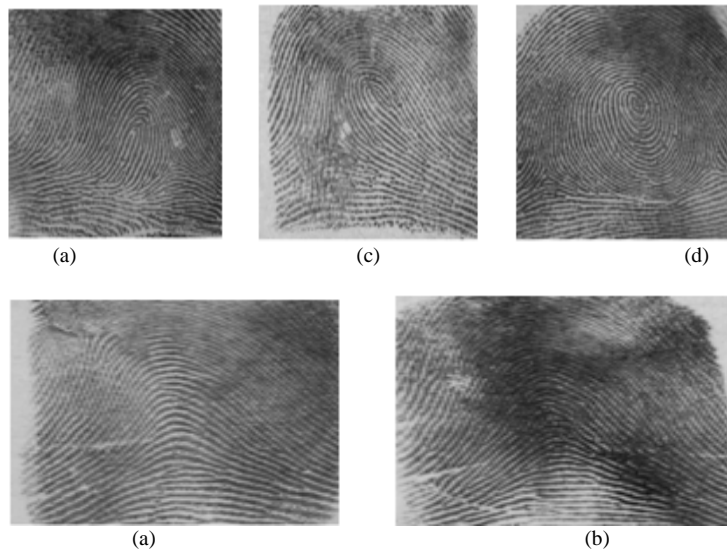

(a) (c) (d)

(a) (b)

Fig. 4. Example of tested samples, (a) Left-loop, (b) Right-loop, (c) Whorl, (d) Arch and (e) Tented-arch
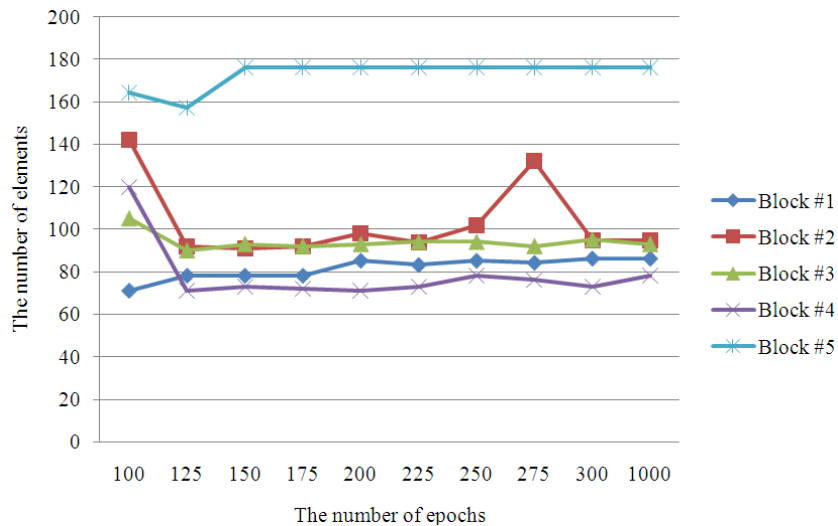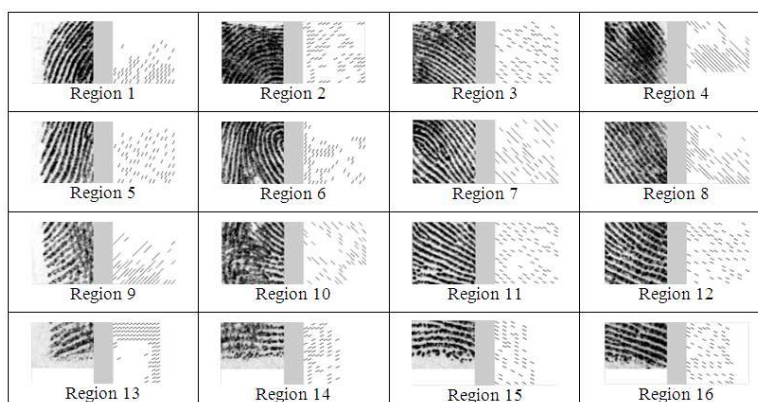

Fig. 5. The optimum of the number of epochs

Fig. 6. The estimation of orientation field of each region

Table 2. The dominant of the number of epochs

Number of epoch										
Block	100	125	150	175	200	225	250	275	300	1000
Block #1	071	078	078	078	085	083	085	084	086	0086
Block #2	142	092	091	092	098	094	102	132	095	0095
Block #3	105	090	093	092	093	094	094	092	095	0093
Block #4	120	071	073	072	071	073	078	076	073	0078
Block #5	164	157	176	176	176	176	176	176	176	0176

Table 3. The most dominant orientation field

Region	Regions' orientation	
	1st rank	2nd rank
1	67.5	45.0
2	22.5	45.0
3	135.0	112.5
4	135.0	112.5
5	45.0	67.6
6	90.0	67.5
7	135.0	112.5
8	135.0	112.5
9	22.5	45.0
10	22.5	112.5
11	112.5	22.5
12	112.5	135.0
13	0.0	22.5
14	0.0	22.5
15	0.0	157.5
16	0.0	22.5

5. CONCLUSION

We propose a new method to estimate fingerprint orientation field. Fingerprint images are divided into 16 regions. Then, each region is divided into blocks of 8x8 pixels to generate a matrix feature. A feature of each block is then generated by summing pixel intensity values of each row and column. The feature matrix is then fed into the SOM network to determine the dominant gradient of each block. The most dominant gradient of blocks represents the orientation field of the region. We used the orientation field of regions to built the prior knowledge. The result of our experiment shows that the chose feature is simple so that the training process of the SOM is very fast; it needs only 125 epochs to be steady. Furthermore, the method can correctly estimate the ridge orientation in most regions.

Unlikely another methods, our method does not need any preprocessing or complicated mathematics calculation. These make the estimation process is simpler and faster. However, the drawback of the method is less precise to estimate the orientation of ridges that were located in regions that are dominated by background pixels.

6. ACKNOWLEDGEMENT

7. ADDITIONAL INFORMATION

7.1. Funding Information

7.2. Author's Contributions

Sri Suwarno: Preparing data and writing the manuscript.

Subanar: Analyzed data using wavelet.

Agus Harjoko: Worked in image data.

Sri Hartati: Analyzed data using SOM.

7.3. Ethics

To the best of our knowledge, there has not been any literature that proposes a method that similar to our method.

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