

Local Descriptor Approach to Wrist Vein Recognition with DVH-LBP Domain Feature Selection Scheme

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Abstract— Local Binary Pattern (LBP) is one of the well-known image recognition descriptors for texture-based images due to its superiority. LBP can represent texture well due to its ability to discriminate and compute efficiency. However, when it is used to describe textures that are barely visible, such as vein images (especially contactless vein), its discrimination ability is reduced, which leads to lower performance. LBP has extensively been implemented for features extraction in recognition system of hand, eye, face, eye, and other images. Nowadays, there are a lot of developments of hand recognition systems as a hand is a part of the body that can be easily used in the recognition process and it is easier to contact the sensor when taking the image (user-friendly). In particular, a hand consists of various parts that can be used, such as palm and fingers. Other parts like dorsal and wrist can also be used as they have unique characteristics, i.e., they are different from each other, and they do not change with ages. Changes in pixel intensity can be derived from skeletal vein images to distinguish individuals in palm vein recognition. In the previous paper, we proposed a method diagonal, vertical, horizontal local binary pattern (DVH-LBP) for implementing the palm vein recognition system successfully. Through this work, we improve our previous procedure and implement the improved method for recognizing wrist. In particular, this study proposes a new and robust directional extraction technique for encoding the functions of the wrist vein in a simple representation of binary numbers. Simulation results show the low equal error rate (ERR) of the proposed technique is 0.012, and the recognition rate is 99.4%.

Keywords— wrist vein; pattern recognition; feature extraction; diagonal; vertical; horizontal local binary pattern (DVH-LBP).

I. INTRODUCTION

The human identification system is indeed a very complex system where many physical and behavioral traits can be used. A vein is one of the physical characteristics that can be used for authentication. According to the literature, vein biometrics research works mostly deal with the problems of hand recognition, such as the palms and fingers of the veins, but very few papers discuss the wrist veins. This paper proposes to use our previously proposed method, which was successfully used for palm recognition, to be implemented for a wrist vein recognition system. Firstly, we introduce and discuss the local binary pattern (LBP)-based wrist vein extraction techniques. It has been stated that this technique can well compensate for the problems of vein patterns with scaling and rotation in a more computationally efficient way. The DVH-LBP algorithm was proposed in [2] where the algorithm uses four cross-correlation operations on neighboring pixels to compensate for rotation operations. The vein database used is also required for preprocessing adopted from the contrast limited adaptive histogram equalization (CLAHE) method. This method has been

proven to be successful in improving the stability of the extracted vein patterns.

The wrist vein recognition as a biometric system for personal identification discussed in this paper. Specifically, novel feature extraction based on the Diagonal, Vertical, and Horizontal local binary pattern (DVH-LBP) for wrist vein recognition is proposed. Note that wrist vein segmentation is not required due to the prominent region of images.

This paper is ordered as the following steps. Section II elaborates the currently available systems of recognition. Section II the method to propose, covering the process of enhancing an image, extracting feature, and matching, and talks about the novel feature extraction. Experimental details and results appear in Section III. Eventually, and the overall conclusions are drawn in Section IV.

II. MATERIAL AND METHOD

A. Related Work

Veins have a unique property in the visual structure, which means that they are different from each other [42]. Some literature studies have conducted research on vein patterns recognition which comprise palm veins [3] – [7], veins of hand dorsal [9] – [13], veins of finger [12], [14] –

[18], veins of wrist [19], [33] – [40], forearm veins [20], and scleral veins [21], [22].

Palm print recognition systems have been widely developed as biometrics recognition systems. However, a palm print may be easily damaged [8]. Therefore, we prefer to use intrinsic biometrics like the retina, palm vein, wrist vein, and hand vein instead of extrinsic ones. In addition, they offer some advantages because they are easy to use, they have in-built liveness detection, and they can be captured through a contact-free process [5]. To obtain suitable vein characteristics, we need to do feature extraction process. There have been some feature extraction methods available in the literature which will be summarized below.

A few geometry-based methods have been discussed in [5], [17], and [26]. The geometry method depends heavily on the selected coordinate system. Specifically, the technique uses approximate line-like, curve, and point information derived from fingerprint and palm print recognition. In this method, we must consider in advance the region of interest (ROI) for calibration of the extraction and position. Geometry based approach has some disadvantages in extraction, representation, and matching. Besides, some information losses which cause small and blurred textures may occur. This makes the method has a poor performance in terms of the different ability and sensitivity to scaling, rotation, and displacement.

The second method uses statistical information so that it is called statistical-based method [6], [7], [15], [27]. The information based on statistics can be in the form of moments or locally stored binary histogram [7]. Furthermore, the statistical-based method may also be classified as global and local. We note that LBP [15], local derivative pattern (LDP) [6], and their variants [7] belong to the local statistical-based method. The local statistical purposes also include scaling, rotation, and displacement sensors. However, the global analytical technique, such as invariant moments [27], is invariant for some operations, such as gradient fields, scaling, displacement, rotation, and wavelet moments, etc.

Some methods that are local invariant-based have been thoroughly studied [28] – [30]. The local invariant process, which emerges from computer vision, such as Scale Invariant Feature Transform (SIFT), Speeded-up Robust Features (SURF), extracts local invariant features directly without having the preprocessing stage. However, this method lacks grayscale shifts and corners so that the local invariant features number obtained is small, and changes in the intraclass are observed. To overcome these problems, image improvement should be carried out in advance of local invariant methods.

Some appearance-based methods such as Linear Discriminate Analysis (LDA), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Factorization of Local Non-negative Matrix also known as LNMF, Factorization of Non-negative Matrix or NMF and their kernel versions, and various method (e.g. OPNN) are studied [12], [31] – [33]. The appearance-based method takes subspace coefficients without previous knowledge as features. This method is very dissimilar from the methods formerly discussed so that it can be put into a different group and viewed as a challenge in pattern recognition. Artificial

intelligence and machine learning are commonly used in this method for extracting and classifying the feature.

As discussed in some references, various biometrics identification and problems of recognition, like identifying face [34], recognizing iris [35] have been successfully implemented by the LBP method. Furthermore, LBP possesses an influential feature representation ability. In particular, LBP and modified LBP have been used for the recognition of finger vein [15], [16], [18], dorsal of hand [11], and vein of palm [6], [7]. It was observed in [37] that every area of interest comes with a unique biometric identification involvement using the LBP algorithm. Consequently, weighted LBP was proposed in [34] to improve the performance of recognition.

Vein patterns can classify local areas into three categories, i.e., a small amount (SA), medium amount (MA), and a large amount (LA) [7]. The categorization is done with the help of a supporting vector machine known as SVM that is a classifier that also assigns the weight for each category [16].

To date, there have been not many research papers discussing wrist recognition. Below are several literature studies of wrist recognition. A dataset of wrist vein was proposed in [39]. The dataset was obtained in an infrared band from 30 individuals. The paper also proposed a prototype of a wrist vein image capturing system by using quality measurement. In [33], a large dataset was used in the recognition system. Correctly, for experiments, low-quality PUT vein images have been used. The enhancement was done through the binarization process, followed by correlation for recognition. Additionally, [33] analyzed different segmentation techniques with enhancement using Discrete Fourier Transform (DFT) and correlational based classification. A standard for the dataset of PUT with Gaussian filter for improvements was discussed in [34].

A minutiae system based on the recognition of wrist veins was proposed [38]. The fusion based on chain codes was used for the recognition of wrist veins [37]. Various skeleton fusion levels were used and followed by a chain code. Unlike [37], whereas the wrist vein pattern was extracted by using spectral minutiae after we preprocess the vein images [36]. In addition, it is indicated that a method for extracting and transforming the vein minutiae into a scaled representation with fixed length and translation invariant, which can compensate for the rotation operation [37].

For the preprocessing approach, discretely implemented Meyer wavelet and histogram equalization with adaptive capability were proposed feature extraction using Pattern of Dense Local Binary known as D-LBP showed that it was able to achieve (EER) or the rate of an equal error on 0.79 [23]. Regarding this reason, it is intended to develop a wrist recognition system which is better than that of the D-LBP.

B. Overview Our Purposed Method

This paper proposes a system for the recognition of the bracelet vein. In this case, the CIE database wrist vein images are used. The proposed new recognition scheme for palm veins comprises four basic modules, i.e., acquisition image module, preprocessing module, feature extraction module, and matching module, as displayed in Fig. 1. Every module has a significant part in defining the wrist vein performance match within the system of biometric detection.

Some capabilities of the modules mentioned above are described below.

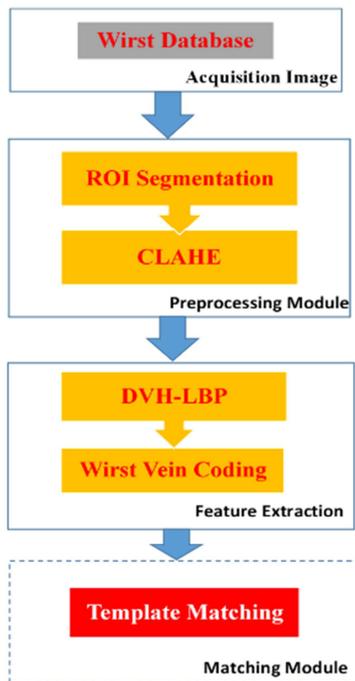


Fig.1 Schematic of the proposed approach.

In the preprocessing process, the CIE wrist image database is obtained from earlier studies using the CLAHE method. This aims to enhance the quality of the images with low contrast. The technique successfully increases the dynamic range of the wrist [32]. Next, resizing image process is done. The process aims to equalize the entire image of the palm

vein, which will be further processed so that it can avoid different features of the palm vein image extraction. In addition, it simplifies the process of cutting the image into smaller regions. In this paper, the size of the vein image to be adjusted is 256 x 256. The vein image is divided into local features before being extracted by DVH-LBP for each region. It takes a feature in the form of a histogram from each area that represents the global feature of the vein image.

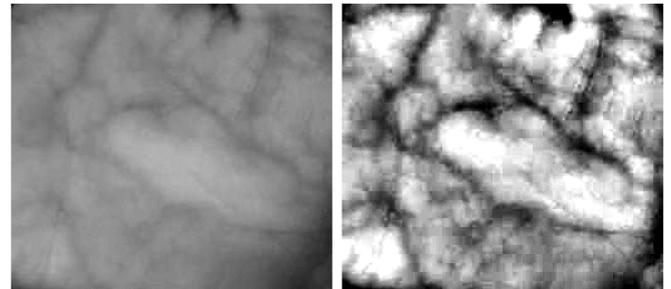


Fig. 2 Extracted ROI image and the enhancement result.

To extract the feature, the pattern of the vein is represented by a Diagonal, Horizontal, and Vertical Local Binary Pattern (DVH-LBP) technique, which will be discussed in Section IV. Patch descriptors of DVH-LBP obtained from every image resulted from the training are implemented to make several feature sets, that is later used for training models production. Support Vector Machines (SVMs) and K-Nearest Neighbors (KNN) are commonly used for classification purposes. A reassuring EER or Equal Error Rate of 0.32 was attained in our experiment.

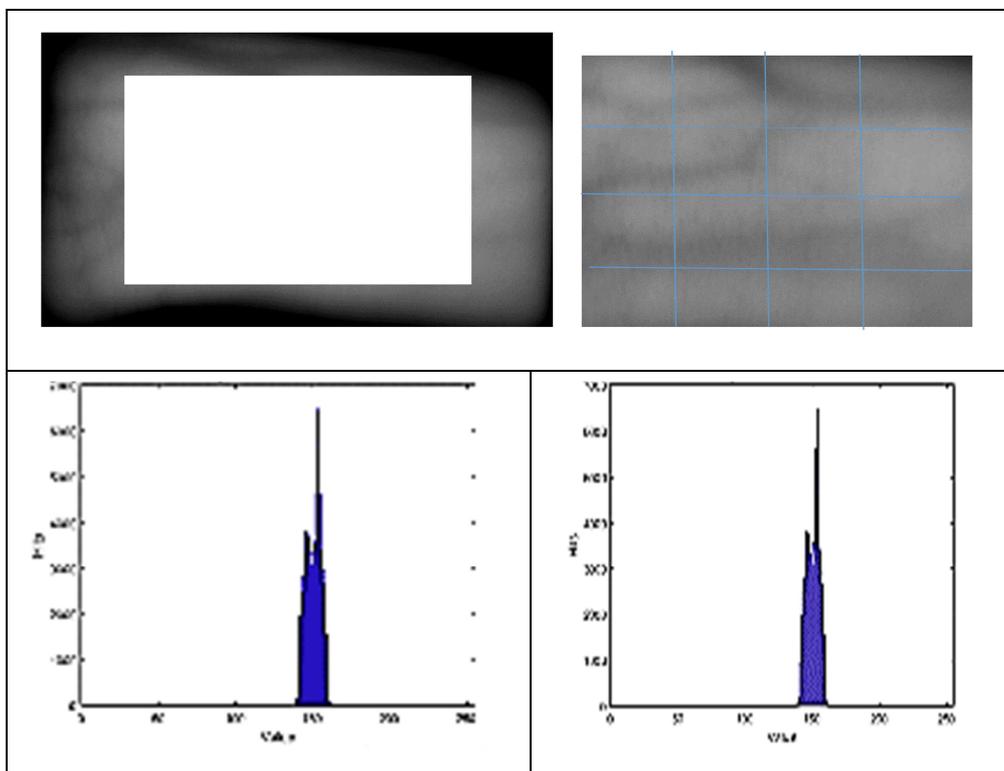


Fig. 3 Histogram of DVH-LBP.

C. Dvh LBP Feature Extraction

The LBP operator labels the pixels of an image by setting a threshold for each pixel's 33 neighbors and binomializes the results into a number [24]. The expression LBP is given by

$$LBP_{P,R}(x,y) = \sum_{k=0}^{K-1} S(g_p - g_c) 2^k \quad (1)$$

Where S is the threshold value, g_p represents each pixel's value, and g_c defines the center pixel value. In (1), P represents the sum of sampling points, while R tells the neighborhood radius.

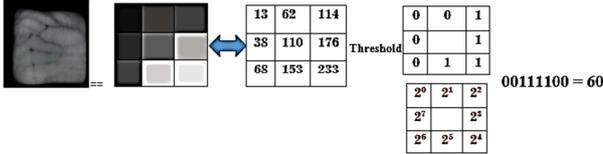


Fig. 4 LBP pattern for a small region [1]

In Fig. 4, the construction of Local Binary Pattern (LBP) conventional micro pattern for a small part is shown. In LBP, each neighbor of the 8(left-top, left-middle, left-bottom, right-top, etc.) is compared to the pixel. We compared them in the clockwise or anti-clockwise direction for each pixel in a cell. If the center pixel value is higher than neighbors, write "0" and "1" otherwise. This process results in a binary number of 8 digits (to make it convenient to do, we usually convert it to decimal). Next, we calculate regarding with the cell the histogram of the frequency of every occurrence "number" (i.e., every combination whenever the pixel size differs from the center). Alternatively, the histogram can be normalized, and all cell types of normalized histograms can be concatenated. This allows use getting the vector of window's feature.

A developed LBP called diagonal vertical and horizontal local binary pattern (DVH-LBP) for texture representation has been proposed recently [2]. Note that for our

convenience, we rename our proposed CLBP in [2] to be DVH-LBP so that emphasizing feature extraction direction can be done. The fundamental concept of DVH-LBP is that the image feature should take the diagonal pixel variations including the front and back diagonal, horizontal and vertical pixel variations in the neighborhood, so that it can perform well, even in the cases of image rotation. The expression of the DVH-LBP is given by

$$DVH_{LBP_{P,R}(x,y)} = \frac{\sum_{k=0}^{|P|-1} (S(g_{|k|} - g_{|P|+k}) 2^{pk} + g_c)}{2} \quad (2)$$

The binary threshold function $S(\delta)$ is given by

$$S(\delta) = \{ (0, \&\delta < 0 @ 1, \&\delta \geq 0) \} \quad (3)$$

Where δ is the difference between the values of front and back diagonal pixels, vertical and horizontal pixels.

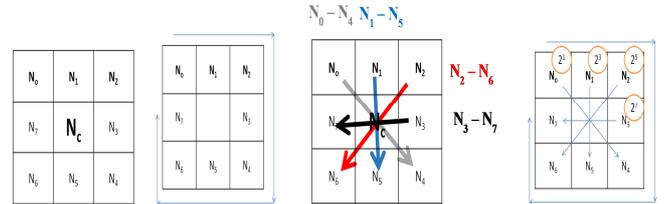


Fig. 5 Arrangement of micropattern DVH-LBP for a small region.

Each patch of DVH-LBP descriptor resulted from every training picture is functioned to create features variation to create a model. Each image is split into 9 windows to extract the patch descriptors (the window value is selected by analysis, the window value which produces the best result is used) and it is also split the locations into patch sizes of 9 x 9 (similarly, the value of the patch is chosen by analyzing the patch value which results in the best result). Next, a bin-size histogram of 256 is calculated for each patch. Finally, each patch's histograms are calculated and the column is intelligently configured to obtain the final descriptor. The LBP and DVH-LBP patch histograms are shown in Figure 4.

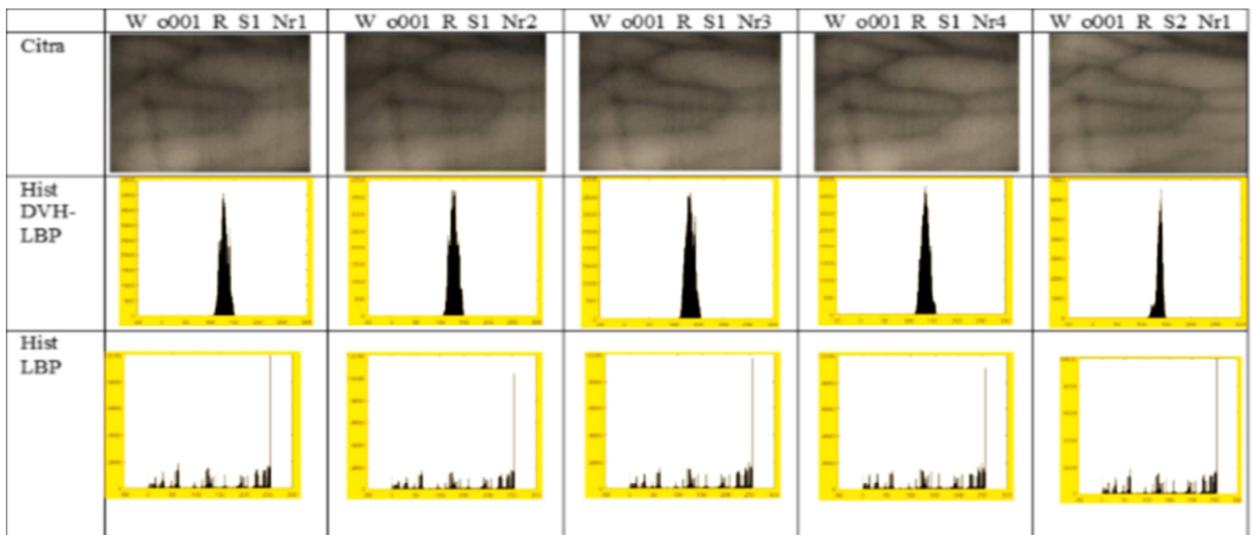


Fig. 6 Comparison Histogram LBP with DVH LBP

After the process of taking the discriminant traits by finding all possible new values from $(DVHLBP_{P, R})$ operations, we take the value that most often arises from the weights that have transitions ≤ 2 .

It can be seen that the transition is less than equal to 2 of the bits produced from DVHLBH only if he has a bit of value less than 2. This formula is defined as.

$$U(DVHLBP) = U_{DVH}(x, y) = \sum_{k=0}^P DVH_{x,y,k} \quad (4)$$

$$U(DVH(x, y)) = \begin{cases} DVH & U_{DVH} \leq 2 \\ 4P + 4 & otherwise \end{cases} \quad (5)$$

If $U(DVHLBP)$ is smaller than 2, the current pixel will be labeled using an index function, $I(z)$. Otherwise, it will be assigned the value $(4P+4)$. So the new histogram and table that is formed can be seen in the picture below, which is from $U(DVHLBP_{P, R})$ that has a bin class along 0-212 after the uniform pattern operation is done, so it becomes 36 class.

D. Support Vector Machine (SVM)

The Vector Machine Support (SVM) [25] is used in this work for classification purposes. SVM is a popular machine learning technology that implicitly carries out a mapping into a function space coming with a higher dimension. After mapping, a linear hyperplane with maximum margins separating the data derived from the space of higher dimension is found. In this paper, the Vector Machine Support Library (LIBSVM) is used for the implementation of the SVM. Although several fresh kernels are offered, the kernel functions mostly used are commonly linear, radial base function (RBF), and polynomial. Note that RBF kernel uses this work.

E. K-Nearest Neighbour Algorithm (KNN)

The (k-NN or KNN), k-nearest neighboring algorithm, represents an object classification method which observes the learning data that are closest to the object. Learning data are projected into a large space in which each dimension is a data feature. Space is divided into several parts according to the learning data classification. A spot in this area is noted as a class center when the class center is the classification mostly found on the neighbor in the nearest area. Usually, close neighbors are computed using the range from the Euclidean. This algorithm only stores the function vectors and the classifications of the learning data during the learning phase. The same features are calculated for the test data during the classification phase (whose classification is not known).

The distance to the entire learning data vector from this new vector is calculated, and a number of the closest k pieces are taken. The new classification point is expected to be included in these points' highest classification. The best k-value depends on data for this algorithm. Generally, the noise effect in the classification process will be reduced when we use high k-values, but it will blur the boundaries between each classification. Ethical k values can be selected with the optimization of parameters, e.g. using technical cross-validation. When the classification is predicted based on the closest learning data (or $k = 1$), it is called the nearest neighboring algorithm.

III. RESULT AND DISCUSSION

In this section, the experimental setting and the output of the work proposed are discussed in detail.

A. Data Set

PUT Vein dataset [41] is utilized in our experiment. The database provides images with high resolution of (1024 x 768). Note that the whole images, in the 460-850nm NIR spectrum, are obtained.

B. Equal Error Rate

Experimental results show a condition where the rate of equal error (EER) of the DVH-LBP is smaller than that of the LBP. The overall experimental results are summarized in Figs. 7– 10.

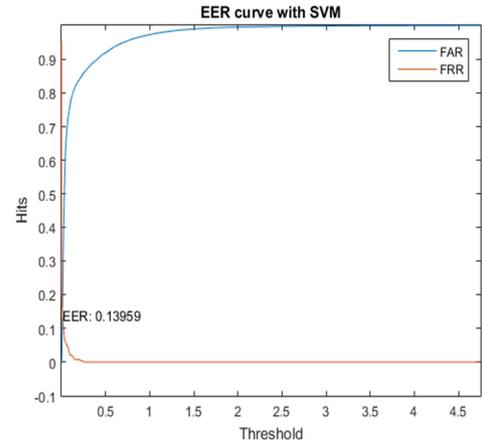


Fig. 7 EER LBP with SVM.

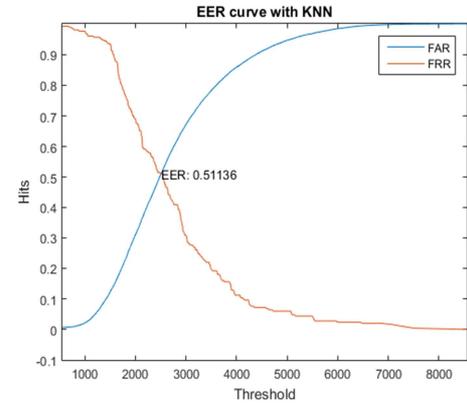


Fig. 8 EER LBP with KNN.

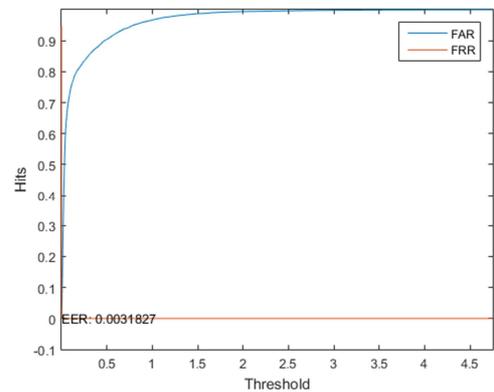


Fig. 9 EER DVH-LBP with SVM.

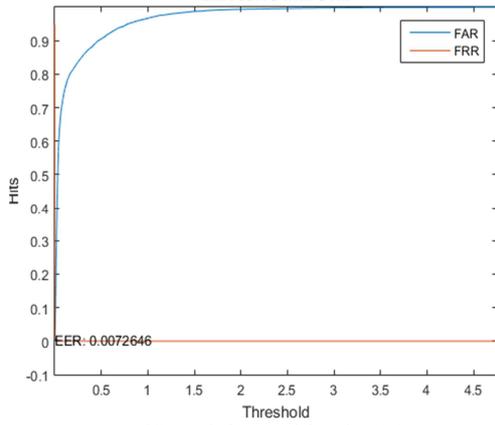


Fig. 10 EER DVH-LBP with KNN.

A. Comparison Accuration LBP vs. DVH-LBP for Wrist Recognition

TABLE I
COMPARISON ACCURATE LBP VS. DVH-LBP

TRAINING: TESTING	ACCURATION (%)			
	LBP		DVH-LBP	
	SVM	KNN	SVM	KNN
3:3	99.2	99.2	99.6	100
5:5	99.2	99.2	99.4	99.6
5:5 (ROTATED)	81.6	80	99.2	99.2

The result in Table 1 showed that both LBP and DVH LBP have almost the same performance for the standard image. But for the case of rotated images, DVH-LBP presented significant improvements in accurate. Then if we appearance the time required for extraction of features in figure 10, it showed DVH-LBP leading. From the 10 images tested, we can find out the elapsed time used to extract features from the wrist images. All the simulated data are obtained by using Matlab with Intel I7 Processor in the windows environment. The results are depicted in Fig. 11. The figure shown that DVH-LBH has the best extraction feature time compare to another wrist vein method [23] and LBP conventional.

B. Comparison EER with the most recent state of Wrist Vein Recognition

Table 2 shows the performance comparison with the available methods in the literature (EER).

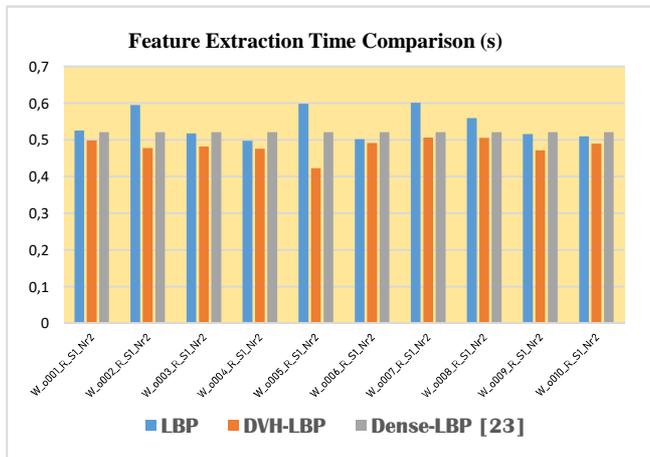


Fig. 11 Extraction feature time comparison

TABLE II

COMPARISON EER WITH STATE OF THE ART

WORK	EER
Kabacinsky et al. [34]	3.51
Kabacinsky et al. [35]	2,19
Kabacinsky et al. [36]	3.8
Abhijit Das [23]	0.79
Proposed Method	0.32

Based on Table 2, the results of the proposed method is superior compared with several similar works found in the literature

C. Comparison EER with State Of The Art of Hand Vein

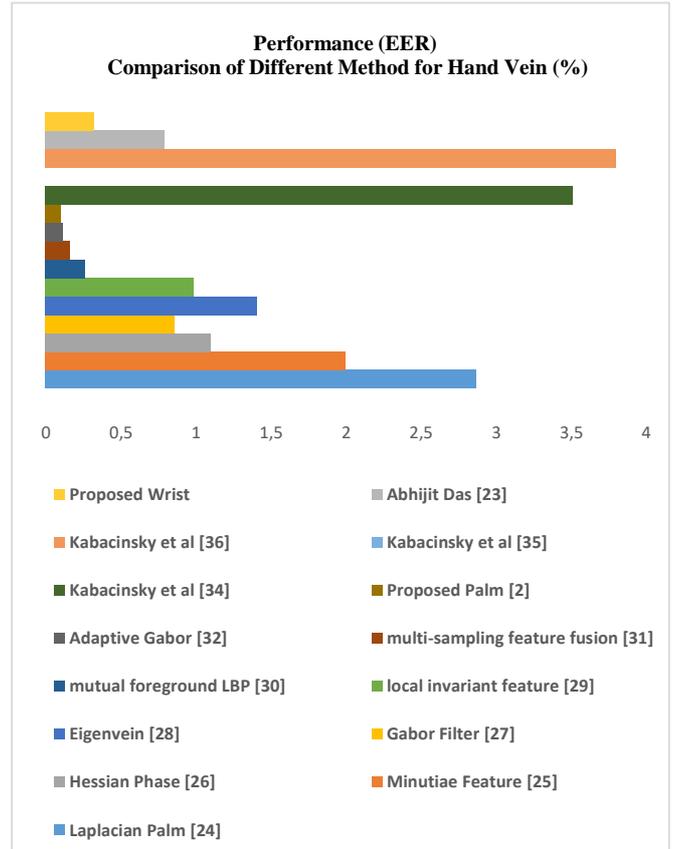


Fig. 12 Comparison EER with State Of The Art of Hand Vein

As shown in figure 12, our proposed method has a good EER even though it is not best compared to other methods used in recognizing palm, dorsal and wrist vein according to the literature studies that have been conducted.

D. Time Complexity

As shown in Table 3, the proposed method in this study has less EER in comparison with the one discussed in [23].

TABLE III
OPERATIONAL EFFICIENCY OF DIFFERENT ALGORITHMS

Method	Mean	Feature Extraction(s)	Matching(s)	Sum (s)
Abhijit Das [23]	22500 (150x150pixels)	0.311	0.25	0.561
Proposed Method	62.536 (256x256pixels)	0.12	0.27	0.39

The result through the experiment describes that the proposed method has computation time of 0.12 second for the feature extraction step, which elaborates that the method proposed is the most efficient among other existing methods. Furthermore, the computation time of our proposed method is 27 seconds in the feature matching step. We also note that our proposed scheme requires additional time for the template matching step. However, we believe that our proposed system still meets practical application requirement as, from the system reckoning, the total consumption time used in our method is only 0.39 second.

In this report, we also analyzed the algorithm complexity. The core code's time complexity of the steps of extraction of the feature is $O(n)$. N represents the sum of algorithm steps because the "main orientation estimation" function should do a function extraction in each direction. In addition, the "Displacement Compensation" function in the core function matching step code must be called iteratively up to $n \log n$ times. The time complexity for this step is, therefore, $O(n^2)$, which shows higher calculation time requirements. It is also noted that the iterative KNN and SVM methods may take longer. The improvement of the algorithm will in future, be considered by introducing the computing technology set in parallel in order to get a faster process of feature matching. Our study in the future will try to reduce the time of calculation by optimizing the code.

IV. CONCLUSION

We, through our research, have introduced a system of biometric capable of recognizing images of the pattern of bracelet vein of the hands attained with a camera of NIR. CLAHE was used for the preprocessing of the wrist vein. We have proposed an approach to person recognition at the image level by using bracelet images. The texture of the important characteristics of the wrist vein, in particular, is well preserved. Moreover, the difference between the function lines and the areas in the surrounding is improved. We have additionally proposed a new feature, "DVH-LBP," which is obtained by using the local descriptor in the extraction module of the feature. As a more accurate representation of vein images, DVH- LBP has been verified. Our algorithm has been evaluated with the CIE database. The results have shown that the DVH- LBP results better than the Dense LBP [23]. Identification using SVM classification and KNN is achieved in the proposed method. It is also better than the results using KNN. Experimental results have shown that the scheme we introduced achieves yielding performance where the EER is 0.32%. The performance is the highest of the other methods for recognizing wrist vein.

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