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# Finger Vein Biometric Identification Using Discretization Method

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**Abstract.** Over the past years, finger vein identification has gaining increasing attention in biometrics. It has many advantages as compared to other biometrics such as living-body identification, difficult to counterfeit because it resides underneath the finger skin and noninvasiveness. Finger vein feature extraction plays an important role in finger vein identification. The performance of finger vein identification is highly depending on the meaningful extracted features from feature extraction process. However, most of the works focus on how to extract the individual features and not presenting the individual characteristic of finger vein patterns with systematic representation. This paper proposed an improved scheme of finger vein feature extraction method by adopting discretization method. The extracted features will be represented systematically way in order to make classification task easier and increase the identification accuracy rate. The experimental result shows that the accuracy rate of identification of the proposed framework using Discretization is above 98.0%.

## 1. Introduction

Finger vein biometric is a physiological biometric trait that uses vein pattern for individual identification. Every person has unique vein patterns which provides high degree of security where only the vein inside the living finger can be captured. As the finger vein is underneath of the skin, it is difficult to copy and steal. With these advantages, there have been increasing research interest in finger vein identification. Nevertheless, identification of finger vein can be a challenging problem because the acquisition process is affected by numbers of factors such as low quality of finger vein images which is caused by pose, deformation and illumination variations [1]. In practical terms, these variable factors are not regulated, so the acquired images of the finger vein contain unclear regions where there is poor separability between the vein and the non-vein patterns [2]. Matching the noise and irregular shadows from the ambiguous area can influence the identification of finger vein. In recent years there has been an increased interest in exploring methods for performing an effective finger vein identification. At present, many of the research groups continue their work on extracting vein patterns from finger vein [3]. Several finger vein feature extraction techniques have been proposed and one of the methods is the maximum curvature [4]. This method extracts finger vein features by checking the curvature value in the cross-sectional profile of finger vein image. The limitation of this method is that the extracted vein features consists of noise that can affect the identification accuracy performance of finger vein.



This study proposed an improved feature extraction scheme method and additional process that can transform the features representation into a better representation of individual features in order to improve the performance of finger vein identification. This paper is structured as follows: Section 2 describe a brief literature review on the works of finger vein feature extraction. The proposed scheme will be presented in Section 3 and Section 4 will explain the experimental work and findings. The conclusion of this study is discussed in Section 5.

## 2. Related Work

Finger vein identification is a physiological characteristic-based biometric technique which utilises the vein patterns of blood vessels inside a finger. Finger vein features exhibits several advantages where each person has a unique finger vein pattern that provide good distinction between individuals. The vein patterns are permanent, do not change over time and are not easily forged and damaged, which brings other advantages to finger vein identification. Despite the benefits mentioned above, there are challenges still outstanding that need to be improved in order to achieve good finger vein identification performance.

Many methods from various viewpoints, such as region of interest extraction, image enhancement and feature extraction have been suggested to address these challenges. Finger vein feature extraction plays an important role in finger vein identification among these approaches. The performance of finger vein identification largely depends on the feature extraction method. Feature extraction is a key step in finger vein identification. A high-quality feature extraction method is necessary in improving the accuracy of finger vein identification performance. The purpose of feature extraction is to extract distinguishing features from the vein pattern to identify individuals.

A significant amount of work on finger vein feature extraction has been published. Finger vein feature extraction methods can be categorized into four groups of method which are vein pattern-based methods, local pattern-based methods, minutiae-based methods and dimensionality reduction-based methods. Local pattern-based methods extract pixel-based methods for the whole finger region and match the features using a pixel-to-pixel technique. This kind of techniques include local binary pattern [6] and its variants such as local derivative pattern (LDP) [7], local line binary pattern (LLBP) [8] and local directional code [9]. These studies show that these methods able to process in faster computational speed but having difficulty in obtaining optimal binary features. The second category is the minutiae-based methods that extract features such as minutiae points and ridge bifurcations. Examples of this method are the Modified Hausdorff Distance (MHD) with minutiae feature matching [10], Singular Value Decomposition (SVD)-based Minutiae Matching (SVDMM) [11] and key points of the scale invariant feature transform (SIFT) [12]. Nevertheless, this method is very limited minutiae in finger vein images and spurious minutiae in a finger vein image can decrease the performance of identification. The third category is the dimensionality reduction-based methods. It is a method that keeps discriminating information and removes noise by transforming the image to a low dimensional image. The example of dimensionality reduction methods includes Principal Component Analysis (PCA) [13] and its variants, namely Two-directional and Two Dimensional PCA ((2D<sup>2</sup>) PCA [14] and linear discriminant analysis (LDA) [15]. However, these methods may not be practical because additional images are needed to train transformation matrix. When there are new enrolled users, the transformation matrix needs to learn again. Furthermore, if the finger vein database is very large, the training process of projection matrix will be complicated. The final category is based on vein pattern-based methods. Most of finger vein feature extraction methods are mainly based on vein pattern feature extraction. The methods of extraction of the vein pattern were developed based on the finger vein's imaging that the gray value of the vein point is lower than the non-vein points of its neighbor [16]. Furthermore, this method extract features from segmented blood vessels and then match them according to the geometric shape or similarity of vein topological patterns. Many works have been proposed, as the vein pattern-based methods are the mainstream in the extraction of finger vein. Typical methods in this category are mean curvature [17], repeated line tracking [18], maximum curvature [4,19], region growth [20], wide line detector (WLD) [21] and Gabor filter [22]. In vein pattern-based methods, Maximum Curvature method is one of the most used method for feature extraction. In addition, Maximum Curvature method have been shown to be powerful for extracting finger vein features as curvature is sensitive to the valley. This method

has become a benchmark for the newly develop finger vein extraction and comparison methods [5]. Nevertheless, there are also some defects in maximum curvature method. There are gaps or burrs in vein patterns and the position of the vein line extracted varies with the direction used in the extraction [16].

It is worth noting that finger vein feature extraction methods discussed in the previous paragraphs still need more enhancement. Another issue regarding feature extraction that could occur is when the extracted features can lead towards high similarity feature values between features or its classes that can contribute to a lower rate of performance accuracy. The transformation of extracted features by representing them in general feature vector with the intention of proposing uniqueness of each extracted features is required. This can be done by implementing the discretisation method that will represent the features of their own unique values.

### 3. Proposed Framework

A key study in this research is how to obtain and classify the person features of the finger vein to identify the person in order to establish an effective finger vein identification method. The common problem is how to systematically depict certain features extracted in distinguishing a person based on the samples of the finger vein. The importance of this study is the introduction of discretization process to systematically represent the extracted features in order to enhance the identification of finger vein. Therefore, the discretization method is implemented in the finger vein identification system as shown in Figure 1. In this framework, the extraction of features is the combination of the maximum curvature method with the direction feature method (MCDF). The input for the discretization process is the extracted features from the MCDF process.

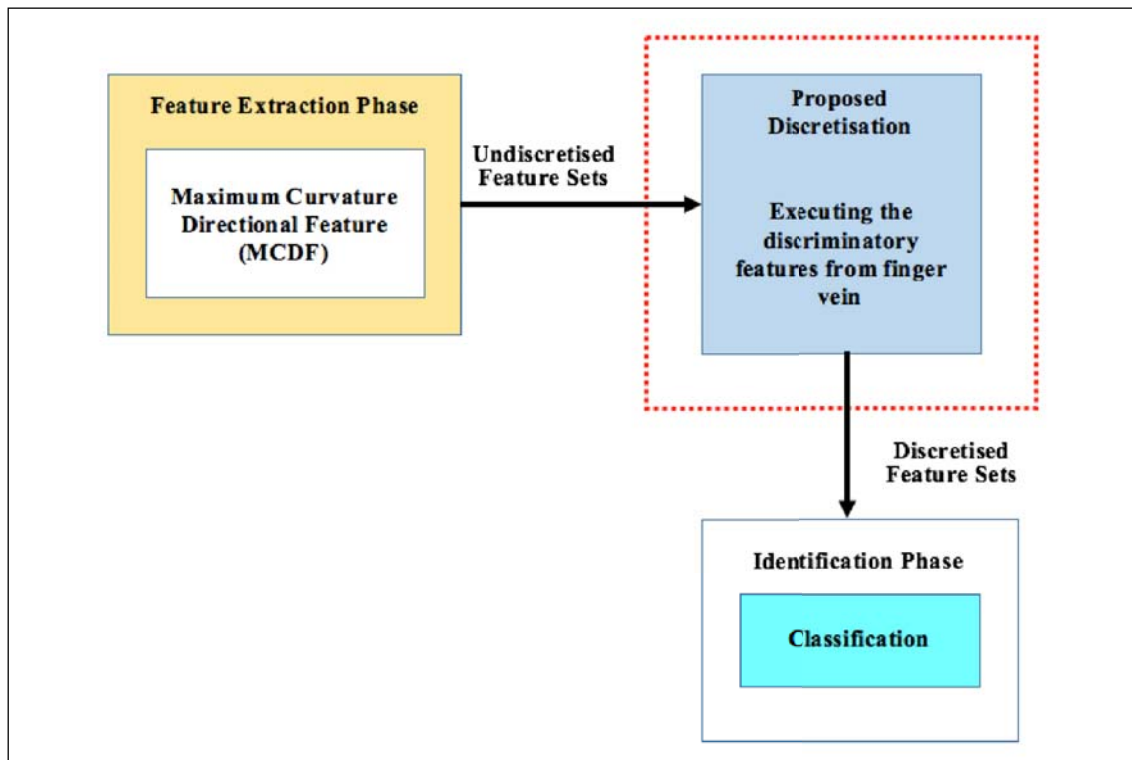


Figure 1. The proposed discretisation scheme for finger identification

### 3.1 Maximum Curvature Feature Extraction

Maximum Curvature is a method of calculating local maximum curvature in cross-sectional profile of a finger vein image. By checking cross-sectional profiles of a finger vein image, the center positions of veins are extracted. Curvatures of profiles will be calculated and the center of vein will be detected. Computation of a score will be assigned to each center positions and all the profiles will be calculated. In order to obtain the vein pattern in an entire image, all the profiles in four directions are analysed. The directions used are horizontal, vertical and the two oblique directions intersecting the horizontal and vertical at 45°. After using the Maximum Curvature approach to obtain the vein pattern, the vein pattern structures are further exploited to refine it. The extracted vein pattern has breakpoints and disconnections. The Directional-Based feature extraction approach is implemented to solve these issues.

### 3.2 Directional-Based Feature Extraction

Directional Feature method implemented in this research study is proposed by [23] and it is originally developed for character recognition. The implementation of this method in finger vein identification scheme is aimed to acquire better informative features to determine the individual identity. In addition, orientation-based finger vein feature representation may reflect better variations in the direction of the finger vein patterns. This approach is capable of extracting the characteristic of vein patterns that concentrate primarily on the vein pattern direction and curve line. In each vein pattern, this approach uses the traversal process and return feature vector as its output.

### 3.3 Discretization

Leng and Shamsuddin [24] defines Discretization as a method of discovering the unique characteristics of a contiguous set of individual samples and then representing them in a standard representation. The representation defines a simple variance of characteristics of similarity between individuals that give maximum discriminative power of differentiate between one person and another. Each discretized vein features data will be used to classify each individual according to the interval representing each value of extracted features adopted by MCDF. First, it will estimate the interval for each individual to represent the real image of finger vein. The number of intervals will be based on the feature vector values. Second, with one representation value, each interval is described. Third, the representation values that have the same values will be clustered into the same interval. The discretization algorithm is illustrated in Figure 2.

```
For each individual {  
  
    Min = min feature; Max = max feature;  
  
    No_bin = no_MCDF_features;  
  
    Interval = (Max-Min) / No_bin;  
  
    For each interval {  
  
        Find lower and upper value of interval;  
  
        RepValue = (upper-lower) / 2;  
  
    }  
  
    For (1 to no_MCDF_features) {  
  
        For each bin {  
  
            If (feature in range of interval)  
  
                Dis_Feature = RepValue;  
  
        }  
  
    }  
}
```

Figure 2. Discretization Algorithm

#### 4. Experimental Work and Results

Several experiments have been conducted using SDUMLA-HMT dataset [25] in order to evaluate the performance of discretization. It is made up of 106 individuals and consists of 636 index finger images. The image is in .bmp format with dimensions of 320 x 240 pixels. The experiment will investigate the improvement of identification performance using the proposed discretisation scheme by utilising different types of classifiers. This section also presents a comparison of identification accuracy between the discretised and the undiscretised data by using WEKA Toolkit. It is to prove the hypothesis of the discretised data can improve the individuality and leads to a better performance of finger vein identification compared to the undiscretised data. The experiment has been conducted to evaluate the identification performance by performing four classifiers. Naives Bayes, Bayes Net, Random Forest and Instance-based classifier with k parameter (IBK) that is using the k nearest neighbour algorithm (K-NN) are the selected classifier schemes in WEKA. The training and testing run on the three finger vein datasets are implemented by using a setup of 60% of training and 40% of testing, 70% of training and 30% of testing and lastly 80% of training and 20% of testing for all classifier scheme. In this experiment, accuracy rate of classification is referred to as performance measure to indicate the competency and efficiency of the proposed discretisation scheme.

#### 4.1 Analysis of Extracted Feature Before Discretization

Figure 3 illustrates the extracted finger vein feature values from MCDF method using SDUMLA-HMT dataset. Zone 1 until Zone 9 represents the extracted features and the individual's id is shown in the last column. It can be observed that there are inconsistent value in the extracted set of features which consists of inter and intra-variability within the samples of finger vein of another person.

In Figure 3, it can be seen from SDUMLA-HMT dataset that the issues of low inter-features variability exist among each sample of different persons. For instance, ID 25 has feature values of 2.0079 which is very close to the feature values of ID 26 which is 2.0077. Whereas, in the first row of ID25 and second row of ID27, the feature values are very close, 2.44821 and 2.44820 respectively. ID27 has feature values of 0.012971 which is high intra-variability from feature values of 7.4588. Good features are important in order to have an accurate performance identification. Apparently, it can be observed that some of the extracted set of features are inconsistent which consists of very close similarity features and high intra-features variability within the samples of finger vein of different persons.

Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7	Zone 8	Zone 9	ID
2.3414	2.44821	5.7884	5.2434	0.89125	1.9875	3.8969	0.33375	3.6726	25
1.8976	2.1149	6.7906	5.4641	0.77897	1.3542	1.0096	0.55641	3.1159	25
2.6749	2.2256	4.789	5.5754	0.89375	1.9432	1.3096	0.66769	3.5615	25
2.3514	2.5595	5.1208	3.1316	0.87965	1.7654	1.1205	0.33436	3.3388	25
2.5637	1.8926	2.5666	4.0201	0.89295	1.8765	3.7865	0.22348	2.6716	25
3.5622	2.0079	2.5672	6.0201	1.2241	0.22246	4.2302	0.22308	3.6723	25
2.5651	1.1225	0.34682	5.5663	3.0089	1.4545	2.3402	1.6732	1.3321	26
0.45434	0.56597	4.9019	3.2325	2.3419	0.78648	2.8966	1.4532	1.9976	26
0.5658	6.1229	4.8119	5.0125	2.0077	2.6752	3.0077	1.1113	1.8776	26
5.9007	3.8964	6.122	3.6732	2.0084	1.6735	5.3466	3.1159	0.33365	26
4.7897	0.78529	3.7894	2.894	2.1181	2.8964	5.5678	3.1162	3.4523	26
5.6795	4.6755	7.9039	0.89384	1.7826	3.1161	5.9007	4.0065	2.7858	26
5.1214	1.6846	2.8935	2.454	8.0159	3.4533	3.4504	1.1138	0.7754	27
3.3429	1.7959	1.5605	3.2338	3.013	4.8979	3.3391	2.4482	1.9875	27
4.2316	1.0174	1.6721	1.1212	5.5694	3.7867	3.5614	1.1137	1.2213	27
0.012971	7.4588	2.339	1.781	6.2349	1.2349	2.8933	0.33543	0.8887	27
4.7911	7.2372	1.6732	0.89264	5.7897	4.7896	2.7633	0.39419	1.7765	27

Figure 3. Pre-discretised data from SDUMLA-HMT dataset

#### 4.2 Analysis of Extracted Feature After Discretization

This section describes the extracted feature values that have been performed with the proposed discretisation. To ensure the uniqueness of individual is preserved, the representation value for an interval is calculated based on the individual class. This is due to the individuality of finger vein where every individual have different vein pattern. The proposed discretization does not change the in characteristic of an individual. It illustrates the connections between features and represent the original extracted features into the discretized features of standard representation In Table 1, the discretised features of finger vein using SDUMLA-HMT dataset is displayed. In the top portion of these tables of each bin, the lower and upper value are recorded in column two and three respectively and the representation values are recorded in column four. The discretised feature values are displayed in the bottom portion of the table. The table shows an example of how the actual features sets from individual are discretised.

Table 1. Discretised Data from SDUMLA-HMT Dataset for Individual No. 25

Discretised Finger Vein Features of Individual 25			
Bin	Lower	Upper	Representation Value
0	0.22256	1.22488	0.501158
1	1.22488	2.22719	1.72603
2	2.22719	3.22951	2.72835
3	3.22951	4.23182	3.73066
4	4.23182	5.23414	4.73298
5	5.23414	6.23645	5.7353
6	6.23645	7.23877	6.73761
7	7.23877	8.24108	7.73993
8	8.24108	9.2434	8.74224

Discretised Dataset									
Zone1	Zone2	Zone3	Zone4	Zone5	Zone6	Zone7	Zone8	Zone9	ID
2.72835	<b>0.501158</b>	5.7353	8.74224	<b>0.501158</b>	<b>0.501158</b>	3.73066	<b>0.501158</b>	3.73066	25
<b>0.501158</b>	1.72603	<b>0.501158</b>	5.7353	<b>0.501158</b>	<b>0.501158</b>	<b>0.501158</b>	<b>0.501158</b>	2.72835	25
2.72835	1.72603	4.73298	5.7353	<b>0.501158</b>	<b>0.501158</b>	<b>0.501158</b>	<b>0.501158</b>	3.73066	25
2.72835	2.72835	4.73298	2.72835	<b>0.501158</b>	<b>0.501158</b>	<b>0.501158</b>	5.7353	3.73066	25
2.72835	<b>0.501158</b>	<b>0.501158</b>	3.73066	2.72835	5.7353	3.73066	<b>0.501158</b>	2.72835	25
<b>0.501158</b>	2.72835	2.72835	5.7353	<b>0.501158</b>	<b>0.501158</b>	3.73066	<b>0.501158</b>	3.73066	25

Discriminatory values of individual 25 for finger vein is <b>0.501158</b>
---

As observed in Table 1, the features values of **0.501158** occur most in the column of the nine features of the SDUMLA-HMT finger vein dataset for ID 25. This means that ID 25 is uniquely recognized by this discriminatory values (DV).



#### 4.3 Analysis of the Classification Accuracy of the Proposed Discretisation Scheme

The performance of discretised data for all classifiers by using three different environment setup using SDUMLA-HMT dataset is shown in Figure 4 and Table 2.

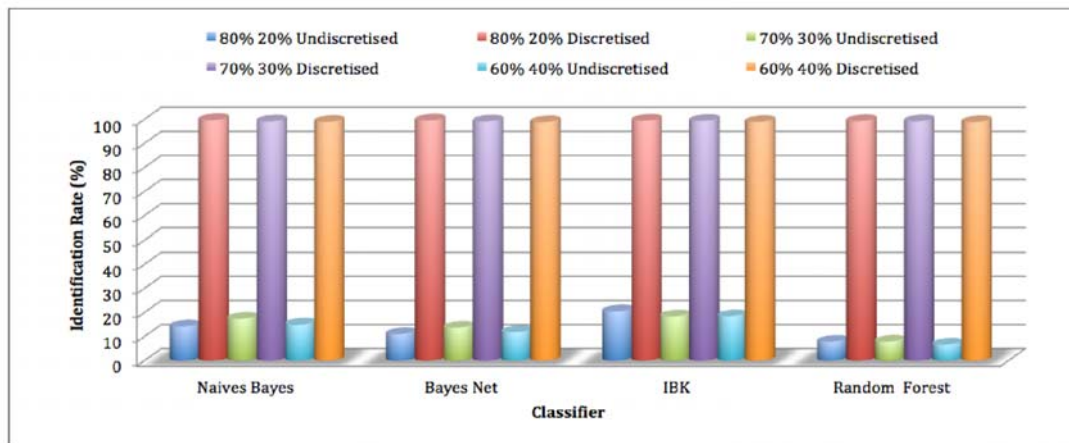


Figure 4 Finger Vein Identification Accuracy Using SDUMLA-HMT Dataset

Table 2 Finger Vein Identification Accuracy Using SDUMLA-HMT Dataset

Classifier	Data Types	80% Training 20% Testing	70% Training 30% Testing	60% Training 40% Testing	Average Accuracy
Naïve Bayes	Undiscretised	14.1732	17.3684	14.9606	15.5007
	Discretised	<b>99.6691</b>	<b>99.1211</b>	<b>98.9315</b>	<b>99.2405</b>
Bayes Net	Undiscretised	11.0236	13.6842	11.8110	12.1792
	Discretised	<b>99.5176</b>	<b>99.1174</b>	<b>98.8189</b>	<b>99.1513</b>
IBK	Undiscretised	20.4724	18.4211	18.5039	19.1325
	Discretised	<b>99.4126</b>	<b>99.3274</b>	<b>98.9189</b>	<b>99.2197</b>
Random Forest	Undiscretised	7.8400	7.8947	6.6929	7.4759
	Discretised	<b>99.2630</b>	<b>99.1737</b>	<b>98.8575</b>	<b>99.0981</b>

Table 2 shows each classifier perform well with discretization data with overall average accuracy of more than 98.0%. The identification average accuracy for Naïve Bayes classifier is 99.2405%, Bayes Net classifier is 99.1513%, IBK classifier is 99.2197% and Random Forest classifier is 99.0981%. However, four classifier methods using undiscretised data reports a worse performance which provide low average

identification rates which is 15.5007% for Naïve Bayes classifier, 12.1792% for Bayes Net classifier, 19.1325% for IBK classifier and 7.4759 % for Random Forest classifier. For clearer picture, the comparison with the proposed discretisation and conventional system is presented in Table 3. The proposed method successfully achieves more than 98.0% on an average when compared with every finger vein dataset.

Table 3. Comparison of Identification Accuracy on Each Finger Vein Dataset

Finger Vein Datasets	Conventional System (%) (Without Using Discretisation)	Proposed System (%) (Using Discretisation)
SDUMLA-HMT	13.5121	<b>99.1774</b>

This illustrates that the proposed framework using discretisation is much competent than conventional system where it able to represent the finger vein features in much better way and could provide higher discriminative in individual identification. Furthermore, there is an improvement in the individual identification performance after performing the discretisation process.

## 5. Conclusion

In this research, finger vein biometric identification using discretization is proposed. The proposed method able to enhance the finger vein identification accuracy performance by 98.0% compared to without using discretization. The discretization method able to distinguish of an individual without losing the features of an individual.

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