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Personal Identification using Local and Global Feature of Finger Vein Patterns using SVM Based Classification

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Abstract— Personal identification and/or authentication using finger vein pattern is becoming most reliable biometrics in many system securities because of its security, accuracy and convenience. The finger vein pattern based biometrics uses human's vascular/vein pattern for their unique identification based on the fact that every individual has distinct veins pattern in their fingers. Finger vein pattern biometric trait is robust against the forgery and does not affect due to external factors since it is inherent and hidden under the skin. Therefore, finger vein pattern based biometrics has gained lot of attention of many researchers. This research paper present an approach designed for personal identification using local and global combined features of finger vein pattern. The finger vein pattern local features are extracted using Local Line Binary Pattern and global texture features are extracted using Discrete Wavelet Packet Transform jointly. Feature level fusion method is adopted for constructing the combined feature vector. Then, Support Vector Machine (SVM) based supervised learning algorithm is used for the feature matching and classification. Experiments are conducted using proposed approach on the finger vein image database of Shandong University, China. The experimental results show that proposed approach outperforms the other methods in terms of the recognition accuracy and performance.

Keywords—Finger Vein Recognition, Local Binary Pattern, Line Binary Pattern, Discrete Wavelet Packet Transform, Support Vector Machine (SVM)

I. INTRODUCTION

Recently, biometric based identification and/or verification have been widely used in many applications such as physical access control, information security, crime detection, banking security, national ID systems and government benefits distribution [1]. However, importance of reliability and security in identification and/or verification has gained lot of attention recently. Because, many extrinsic biometric traits such as fingerprint, palm print, and face features are more vulnerable against spoofing and can be forged with the moderate efforts [2]. Therefore, reliability and security is becoming major issue against such biometric trait based identification. Finger vein pattern is a newly emerged biometric trait which has gained many researchers attention as the promising alternative for identification [3]. The vein pattern biometric uses human's vascular pattern for the personal identification based on the fact that every individual has unique vein pattern. Medical studies have also proven that the vein pattern in every individual is unique and stable for long period of time [3]. The arteries and veins aligned into the subcutaneous layer of the human skin transports the blood throughout the human body to maintain the metabolism process [4]. These veins network image cannot be captured using normal camera since it is hidden under the skin. Therefore, near infrared cameras with 740-960nm wavelength are used for capturing the finger vein pattern images. As infrared light passes through the finger skin, deoxygenated haemoglobin in blood veins strongly absorbs the infrared light rays and reflects the vein line network as the dark lines and other parts as bright into resultant image [4], [5]. This dark line vein network is extracted and used for the pattern feature extraction which is further used for unique identification of the person. As finger vein pattern is an intrinsic biometric trait which is hidden under the skin, it is robust against the forgery, spoofing. This trait does not affect due to external facts such as injury, dirt, moisture since vein pattern image acquisition is contactless [5], [6]. Moreover, finger vein pattern of only live person can be captured because only live body circulates the blood to maintain the metabolism and vein pattern information disappears when tissues loses the aliveness. Therefore, finger vein trait is becoming most reliable biometrics for personal identification and/or authentication due to its accuracy, security and convenience [3], [6], [7], [8].

II. Related Work and Motivation

The finger vein pattern feature extraction and recognition related existing research work available in the literature is discussed as follows.

In [9], Miura et al. developed a repeated line tracking algorithm for extracting the finger vein pattern features. This line tracking process starts randomly from any pixel and moves pixel by pixel through dark vein line in a finger vein image. Experiments conducted on 678 different finger images shown 0.145% as equal error rate (EER) and 460 ms as response time. Thereafter in [10], He designed another algorithm for reducing the EER of repeated line tracking method by extracting the maximum curvature points from the cross sectional profile of the finger vein image.

In [11], Cheng-Bo et al. proposed an approach to extract the vein pattern shape features using minutiae points such as bifurcation and ending points from the given finger vein pattern images. Then, Modified Hausdorff Distance (MHD) was used for matching the relative positions of finger vein shapes. Experimental results have shown 0.761% as equal error rate at 0.43 HD distances threshold value.

In [12], Eui Chul Lee et al. designed a method for extracting the minutiae points and affine transform was used for its alignment. Then, Local Binary Code (LBP) code of these aligned minutiae points were combined for creating the feature vector. Experiment was conducted on data set of 60 persons with 8 samples of each had shown the 0.081% as EER and 118.6 ms as a processing time.

The existing approaches discussed above uses segmented veins network structure from the given finger vein images for unique features extraction and recognition. These approaches provide the good recognition results if segmentation is done accurately. However, performance of the recognition is degraded due to improper segmentation vein network from the poor quality finger vein images because of the optical blurring and skin scattering problems. Moreover, finger veins network segmentation is also affected by translation and rotation in to input finger vein image. To overcome the problems faced by minutiae and curvatures based approaches, local binary pattern based methods are researched such as Local Binary Pattern (LBP), Local Derivative Pattern (LDP) and Local Line Binary Patterns (LLBP) for extracting the local pattern based feature codes from finger vein images.

Local Binary Pattern (LBP) based method uses square shaped neighbourhood mask for extracting the binary pattern code for the given input images and this unique code was used for the recognition purpose. In [13], Rosdi et al. proposed a new variant of the LBP operator called as Local Line Binary Pattern (LLBP) which uses the line shaped mask because veins are aligned under the skin in the line style. The line shaped mask LLBPh and LLBPV in horizontal and vertical direction respectively was applied on the finger vein images for extracting the unique codes of vein lines along horizontal and vertical directions. Then, magnitude LLBPm is computed by taking the combination of LLBPv and LLBPh codes. Experimental results have shown the better recognition results than the LBP and LDP methods.

The other category of finger vein pattern features extraction from the literature is Gabor filter which extracts the global texture features oriented at different orientations from the finger vein images. In [14], Jinfeng Yang et al. designed a bank of Gabor filters for exploiting the finger vein features at different orientations and scales. Then, the finger vein code is constructed based on the Gabor filtered image and cosine similarity measure was used for the classification purpose.

In [15], Kejun Wang et al. designed four 2D Gabor fitters for filtering an input finger vein image and the phase and directional vein pattern features were extracted from the vein pattern. Then, Modified Hamming Distance based classification method was used for the similarity measurement. The Gabor filter based approaches provide good recognition results but with high computational complexity since Gabor function is not an orthogonal basis set and their representation is not compact. Due to this, Gabor filter method requires more computations and more memory space for feature extraction and matching in the classification stage.

Based on the literature analysis, it is observed that vein structure or minutiae based approaches faces the challenge in segmentation of accurate vein network from poor quality finger vein images. Gabor filter based method requires high computational and memory storage. The local pattern based methods such as LBP, LDP, and LLBP is found better to overcome the challenges faced by the local minutiae and curvatures based methods. LLBP operator has given better recognition results than the LBP and LBP operators but still the memory and feature matching time required is not reduced. It means each approach has some advantages as well as limitations, no any single approach is found good enough that can extract robust features from the average quality images. Therefore, we motivated to focus on the combination of approaches for constructing the discriminate and robust single feature vector which contributes in the better performance of the proposed method for finger vein recognition.

In order to design the proposed method, local and global features of finger vein pattern are combined together. The local features of finger vein pattern are extracted using Local Line Binary Pattern operator and global textures feature are extracted using the Discrete Wavelet Packet Transform. The LLBP histogram based features and DWPT based global feature combined together to construct the feature vector. Then, SVM based classification method is used for the classification of the finger vein images into the appropriate predefined classes.

The rest of the research paper is organized as follows. Proposed methodology developed for the finger vein pattern feature extraction and their recognition is presented with detail in the Section III. Then, experimental results of the proposed method with the discussion are presented in the Section IV. Finally, the conclusions drawn based on the reported results and discussions are given in the Section V.

III. PROPOSED METHODOLOGY

The proposed method for the finger vein feature extraction and their recognition is designed by combining the features of LLBP method with the Discrete Wavelet Packet Transform based features jointly. Thereafter, SVM based classification scheme is adopted for the classification of combined feature vector of the given finger vein pattern images. Proposed methodology designed for finger vein feature extraction and recognition consist of the stages such as Pre-processing, Feature Extraction and Feature Classification. The procedure of the proposed feature extraction and their classification method is illustrated in the following Figure 1.

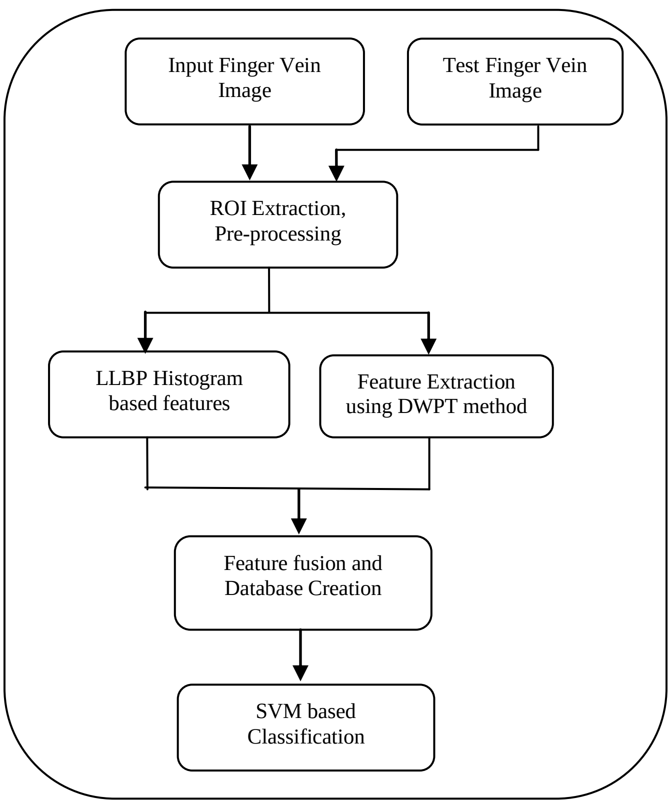

Figure 1. Work flow of the Proposed Method

A. Finger Vein Image Database

The finger vein image database used in this research work is provided by the Machine Learning and Data Mining Lab, Shandong University (SDUMLA), China [24], [25]. This database includes the finger vein pattern images of 34 individuals (20 males and 14 females) who were the students, professors and staff at their school. The index and middle finger of both left and right hand of every individual with 30 different variations of each finger was collected. Consequently, this database consists of the 4080 (34×4×30) finger vein images. The spatial resolution of the finger vein image from this database is a 24-bit colour image with a size of 320×240 pixels. These finger vein pattern images were captured by a device which was designed by the Joint Lab for Intelligent Computing and Intelligent Systems of the Wuhan University.

B. Pre-processing

In pre-processing stage, input finger vein image is processed for segmenting the ROI and enhancing its details for the feature extraction purpose. The veins structure ROI from the whole finger vein image is extracted and normalized using an algorithm given in [24], [25]. The original finger vein images from the database were 24-bit colour with 320x240 pixels size. These original finger vein images are converted into the 8-bit gray scale image and Sobel edge detection operator is used for detecting the edges of a finger from the given finger vein image. Then, the width and height of finger image is computed by using maximum and minimum abscissa values of the finger profile. Then, finger vein pattern ROI is obtained based on these abscissa values and its size is normalized to the 96x64 pixels using the bilinear interpolation [24]. The gray level of extracted vein ROI is enhanced using the histogram equalization method.

C. Features Extraction Method

The proposed method for finger vein features extraction is designed by combining the histogram based features of LLBP method with the DWPT based global texture features. In order to reduce the feature matrix of LLBP method, the first order histogram based features such as standard deviation, absolute mean and entropy are obtained from the LLBP feature matrix. In order to extract the discrete wavelet packet based global features, input finger vein ROI is decomposed by applying the standard 2D-DWT up to third level without considering HH subband for decomposition at each level. Then, the statistical features such as average standard deviation and energy from all the subbands of each decomposition level are computed for feature vector creation. The feature extraction using LLBP and DWPT based methods is discussed below.

1. Local Line Binary Pattern Features

Local Line Binary Pattern (LLBP) is a new variant of Local Binary Pattern (LBP) firstly proposed by Petpon and Srisuk [17] and further Rosdi et al. [13] applied it for the finger vein pattern features extraction. The neighbourhood shape of LBP operator is square but its shape in LLBP operator is horizontal and vertical line which can better extract the vein lines of finger vein images. The horizontal and vertical line masks are called as LLBPh and LLBPv components of LLBP operator. LLBPm is the magnitude of LLBP operator obtained by computing the line binary codes for both the components. N is the number of pixels in the line mask. $\mathbf{h_n}$ and $\mathbf{V_n}$ are the pixels along the horizontal and vertical lines. C = (N+1) / 2 which represents the centre position in a line mask, $\mathbf{h_c}$ and $\mathbf{V_c}$ are the center pixels those are located on the horizontal and vertical line masks. The function $\mathbf{S}(.)$ is the thresholding function for horizontal and vertical line is shown in the equation (4) and (5) respectively [17].

$$LLBP_{h,N,c}(x,y) = \sum_{i=1}^{c-1} s(h_i - h_c) * 2^{c-i-1} + \sum_{i=c+1}^{N} s(h_i - h_c) * 2^{i-c-1} \quad (1)$$

$$LLBP_{v,N,c}(x,y) = \sum_{i=1}^{c-1} s(v_i - v_c) * 2^{c-i-1} + \sum_{i=c+1}^{N} s(v_i - v_c) * 2^{i-c-1} \quad (2)$$

$$LLBP_m = \sqrt{LLBP_h^2 + LLBP_v^2} \quad (3)$$

$$S(h_i - h_c) = \begin{cases} 1, & (h_i - h_c) \ge 0, \\ 0, & (h_i - h_c) < 0 \end{cases} \quad (4)$$

$$S(v_i - v_c) = \begin{cases} 1, & (v_i - v_c) \ge 0, \\ 0, & (v_i - v_c) < 0 \end{cases} \quad (5)$$

The process of feature extraction using LLBP operator [13], [16], [17] is shown in the Figure 2, and their mathematical expressions are given in the equations (1) - (5).

The LLBPh component of LLBP extracts the line binary code with N-1 bits for each pixel in the horizontal direction using equation (1) and (4). Similarly, LLBPv component extracts the same number of codes using equation (2) and (5). Then, magnitude LLBPm is calculated by combining the LLBPh and LLBPv component for (2N-1) bits using equation (3) [13], [16], [17]. This way the local line binary pattern feature for each pixel is computed and represented into the LLBP feature matrix.

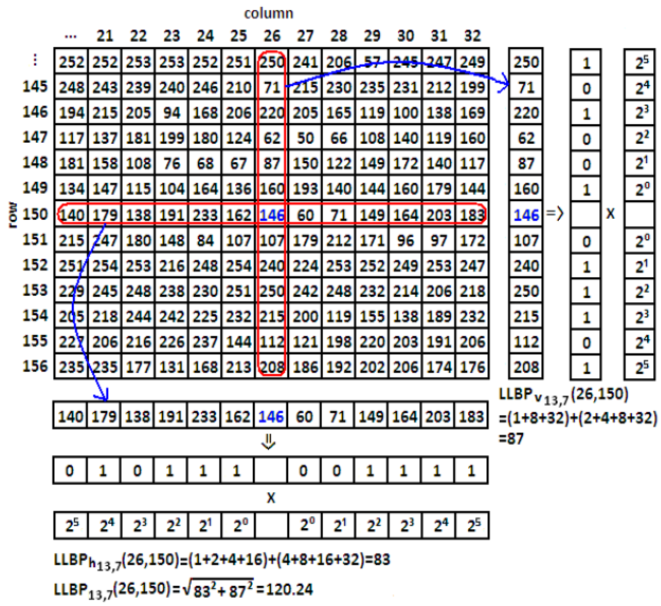

Figure 2. Illustration of LLBP feature extraction process [13]

2. *Discrete Wavelet Packet Transform Features*

Discrete Wavelet Transform (DWT) is a popular mathematical tool used for transforming and analysing the signal into time and frequency domain. The shifted and dilated wavelet functions at {$\Psi 0^0$, $\Psi 90^0$, $\Psi \pm 45^0$} orientations and the scaling function are expressed using equations (6) and (7) respectively [18], [19].

$$W_{\emptyset}(j_0, k_1, k_2) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y)\, \emptyset_{j_0,k1,k2}(x,y) \quad (6)$$

$$W_{\Psi}^{i}(j_0, k_1, k_2) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y)\, \Psi^{i}_{j_0,k1,k2}(x,y) \quad (7)$$

Where i = θ, angles {0^0, 90^0 and $\pm 45^0$} of wavelet function. The standard DWT decomposes an input signal into the four LL, LH, HL and HH frequency channels called as subbands. The LL subband gives approximate coefficients i.e. average image coefficients. Whereas LH, HL and HH subband provides the horizontal, vertical and diagonal information of an image respectively at angle of {0^0, 90^0 and $\pm 45^0$} [18], [19]. This means first two wavelets provide information of an image strongly oriented at 0^0 and 90^0 degree respectively. The third wavelet mixes information from two diagonal orientations such as 45^0 and -45^0. It does not have any dominant direction. In pyramidal DWT, only the LL subband coefficients are decomposed further at each level based on the fact that this subband contains most of the significant information of an image [19], [20]. However, it is stated in literature that some of the significant information may also available in the middle and high frequency subbands. Discrete Wavelet Packet Transform (DWPT) decomposes LL subband as well as LH, HL and HH subbands further at each level which exploits complete information of an image using approximate coefficient as well as detailed coefficients [21]. Therefore, we motivated to use DWPT based method for extracting information from all frequency channels of finger vein pattern images. The third level decomposition of an input image using DWT and DWPT method are shown in the following figures 3(a) and 3(b):

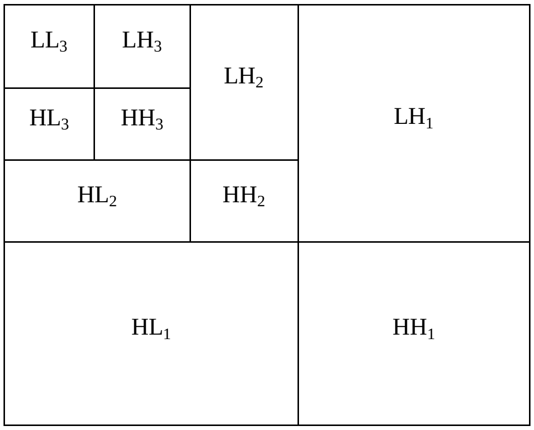

Figure 3(a). 3rd Level decomposition using DWT

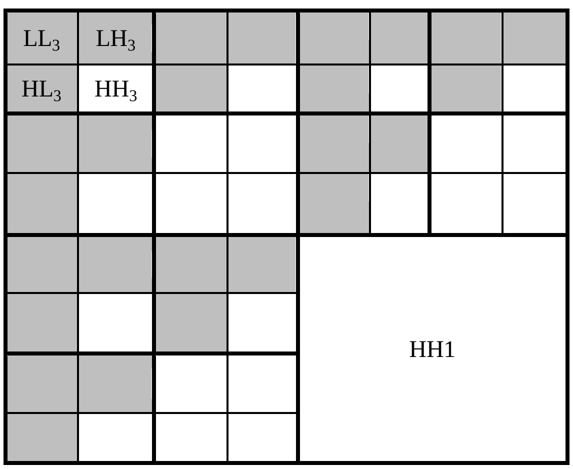

Figure 3(b). 3rd Level decomposition using DWPT

D. Feature Matching and Classification

In this stage, feature vector of test finger vein image is compared with the database image feature vector for the similarity measurement and classification. Proposed method uses Support Vector Machine (SVM) based similarity measurement and classification scheme for classification of finger vein images from the given database. SVM is a supervised machine learning technique generally used for solving the problems of classification. The SVM classifier algorithm finds out an optimum margin hyperplane which can discriminate the data points or patterns of the two classes from each other [27]. In case of the non-linearity in data, SVM transpose the data into the higher dimensional space using kernel functions. This transformation allows discriminating the data points into new space easily [27], [28]. In this research work, SVM built in tool from the Classification Learner of the MATLAB apps is used for classification of the finger vein image from the database. The built in SVM algorithm with different kernel functions using One-Vs-One and One-Vs-All multiclass classification approach is used for the cross validation of the finger vein images from the database.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this research work, experiments are conducted using different feature sets on the existing finger vein image database in MATLAB using SVM of Classification Learner app. The first experiment is conducted using features sets of histogram features of the LLBPm, LLBPv and LLBPh components on the given finger vein image database. Second experiment is conducted using the feature set such as DWT, DWPT All subbands, DWPT with (LL, LH, HL subbands), DWPT with (LH, HL subbands), and DWPT proposed method on the same image database. Finally, third experiment is conducted using combined features of LLBP and DWPT i.e. proposed method on the same finger image database using the SVM of Classification Learner app in MATLAB. The performance of the proposed method using different SVM kernel functions with One-Vs-One and One-Vs-All multiclass classification approach are evaluated using the given finger vein image database. The classification percentage of the histogram based features of LLBPm, LLBPv and LLBPh components using different kernel functions with one-vs-one and one-vs-all multiclass classification approach using Classification Learner SVM algorithm in MATLAB is given in the table 1.

Table 1. Classification Percentage of LLBP Feature Components

Kernel Functions	**LLBPm**		**LLBPv**		**LLBPh**	
	one-vs-one	one-vs-all	one-vs-one	one-vs-all	one-vs-one	one-vs-all
Linear SVM	88.0	88.2	89.3	89.6	86.7	87.0
Quadratic SVM	94.3	94.6	95.0	95.4	92.0	92.3
Cubic SVM	94.5	94.8	95.9	96.0	92.4	92.6
Gaussian SVM	95.6	96.0	96.6	96.8	94.9	95.2

Based on the classification rates of LLBP feature component using SVM based classification method, it is observed that the LLBPv feature component using Gaussian kernel function with one-vs-all multiclass classification approach provides good results than other feature components. The classification percentage of the DWPT features based method using SVM algorithm of the Classification Learners

App with different kernel functions and multiclass classification approach is given in the above table 2. Based on the correct classification rates of the DWPT features based method using SVM based classification, it is observed that the DWPT proposed approach using Gaussian kernel function with One-Vs-All multiclass classification approach gives better classification rate than the other DWPT features approaches.

Table 2. Correct Classification Percentage of Proposed Method with different Cross Validation Folds

Kernel Functions	DWT Only		DWPT with all subbands		DWPT without HH subband		DWPT with LH, HL subbands		DWPT proposed approach	
	one-vs -one	one-vs -all	one-vs -one	one-vs -one	one-vs -one	one-vs -all	one-vs -all	one-vs -all	one-vs -one	one-vs -all
Linear SVM	86.5	87.0	87.5	88.0	89.0	89.0	87.0	87.5	90.0	91.0
Quadratic SVM	91.8	92.0	94.3	94.5	94.4	94.7	92.5	92.5	95.6	95.8
Cubic SVM	92.6	93.0	95.0	95.0	94.5	94.5	92.8	93.4	96.0	96.5
Gaussian SVM	93.0	93.5	95.0	95.6	96.0	96.0	94.2	94.5	97.5	97.5

Therefore, the proposed method for the feature extraction is designed using feature combination of the histogram based features of LLBP component with the DWPT proposed approach features together. Then, combined feature vector of the proposed method is classified using the SVM algorithm of the Classification Learner App in MATLAB. The correct classification percentage of the proposed method using different SVM kernel functions with different cross validation folds and multiclass classification approach is given in the following table 3.

Table 3. Correct Classification Percentage of Proposed Method with different Cross Validation Folds

Kernel Function	2 Folds		3 Folds		4 Folds		5 Folds	
	One-Vs-One	One-Vs-All	One-Vs-One	One-Vs-All	One-Vs-One	One-Vs-All	One-Vs-One	One-Vs-All
Linear SVM	96.0	97.0	98.0	98.0	98.0	98.5	99.0	99.0
Quadratic SVM	97.5	98.0	98.5	99.0	100	100	100	100
Cubic SVM	98.0	98.5	99.0	100	100	100	100	100
Fine Gaussian	73.8	93.5	53.7	82.5	80.6	98.0	83.7	97.0
Medium Gaussian	99.0	99.0	99.5	100	100	100	100	100
Course Gaussian	86.5	95.4	59.8	94.7	88.5	95.0	87.6	92.7

Based on the classification percentage of the proposed method given in table 3 and figure 4, it is observed that proposed method using Gaussian kernel function using one-vs-all multiclass classification approach with 3-fold cross validation scheme gives better classification rates than the other DWPT features approaches. It has been also observed that the cross validation result of the proposed method is optimum and better using the 5-Folds cross validation method using all the SVM kernel functions. The classification performance of proposed method using different folds is shown in following Figure 4.

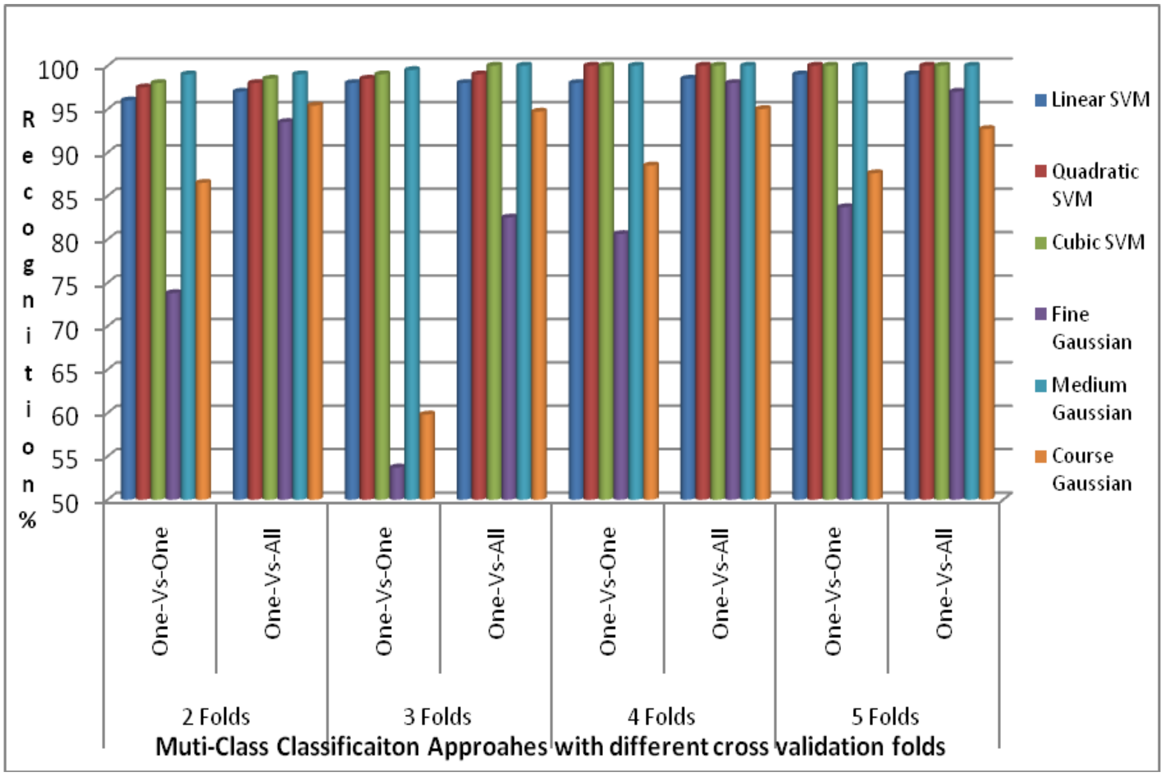

Figure: 4. Classification performance of the proposed method using different kernel function with One-Vs-One and One-Vs-All and different Cross Validation Folds

V. Conclusion and Future Scope

The finger vein pattern based personal identification and/or authentication using their local and global features with SVM based classification is presented in this research paper. The local features of the finger vein pattern are extracted using LLBP features method and global texture features are extracted using discrete wavelet packet transform (DWPT) which gives discriminate features from the finger vein line network. The feature level fusion method is adopted for combining the histogram based feature of LLBP operator with the DWPT based features. Then, Support Vector Machine (SVM) algorithm of the Classification Learner app in MATLAB is used for the classification purpose. The performance of the proposed method is evaluated on the finger vein pattern image database using different SVM kernel functions with One-Vs-One and One-Vs-All multiclass classification approach using different cross validation folds. The experimental results shows that the proposed method with Gaussian kernel function using 3-Fold cross validation approach gives the better classification results than the other approaches. The future extension in this work is to train the different neural network models for classification of the proposed method.

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