# A Perspective of Finger Vein Pattern based Testifying System

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**Abstract**
*Technological development helps us in acquiring and accessing digital data all-round the word. Maintaining high security and data confidentiality is a grueling task. In this paper, a finger vein pattern-based testifying system using Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel is proposed for securing digital data by verifying individuals identity. A six-stage process includes, filtering, enhancing, segmenting, feature extracting, training and classifying the finger vein image was effectuated. Discriminating from the existing approach, a 2D Gabor filter was used for better performance and SVM-RBF classifier for testifying purpose. The analysis was done with different features from which large variation in skewness range between individuals was observed. This Finger vein pattern-based testifying system becomes reliable and easier.*

**Keywords:** *Vein Recognition, Support Vector Machine, Radial Basis Function, Gabor Filter, Gray Level Co-occurrence Matrix, Mathematical Morphology*

## Introduction

As fingerprint, face recognition, Iris scanning being the conventional methods can also be supplemented with finger vein based pattern recognition. Recognizing finger veins works on the principle of Infra-Red absorption. The hemoglobin in the red blood cells of the finger veins absorbs the Near Infra-Red (NIR) light and the corresponding absorbing ranges are captured as image and are considered for the testifying process. As the finger veins being unique, supports in identifying individuals for securing purpose. It also endorse in credit card authentication, automobile security, employees attendance marking, digital system authentication. The NIR led light is passed on through the finger vein and the hemoglobin present absorbs making a dark pattern of lines articulating the actual vein system. The image sensor on the other end records the pattern of veins as images and the acquired data are digitized. These images are considered for authentication and testifying purpose as these blood vessel patterns cannot be counterfeit as located beneath the skin. Many approaches have been proposed from different perspectives for finger vein recognition. In this paper, the Support Vector Machine with Radial Basis Function Kernel (SVM-RBF) was used with the texture properties of Gray Level Co-occurrence Matrix (GLCM) for finger vein recognition. The texture features shows larger variation between vein images and four best features were considered from literature analysis.

## Literature Survey

Guo et al. proposed a research work on finger vein acquisition and finger edge extraction process. The quality of vein pattern was assessed in the acquisition level and the predefined brightness conditions were ensured. The median filter and Gaussian filters were used in the preprocessing level to reduce the noise. Laplace gauss edge detection method was used for edge extraction. Robert edge detection mask along with mathematical morphology had been implemented for vein edge post-processing. Despite producing good result, increase in time consumption was observed as a major drawback [1]. Huang et al. proposed a hardware module for accurate extraction of finger vein image with ARM processor. It extracts the finger vein images from six different locations using CMOS arrays [2].

Ezhilmaran et al. proposed a fuzzy logic-Mamdani approach to locate the finger vein. Edge Pixel Ratio (EPR) was the parameter considered for performance analysis and was compared with other well-known methods such as Sobel, Prewitt, Roberts, Laplacian of Gaussian and fuzzy logic. Appropriate edges of vein images, with comparatively high EPR value were provided by this system [3]. Duque Vehils et al. proposed a Support Vector Machine (SVM) finger vein identification system. The work encompasses image acquisition, fuzzy-based vein segmentation, feature extraction, and matching. The veins width were reduced to one pixel by thinning process with eight kernels. Cross point, endpoint, maximum distance value, and minimum distance value were the features used to train and classify SVM [4].

Dharmadhikari et al. proposed a human identification system which used the line tracking algorithm to extract the vein pattern with certain number of iterations. The smoothening and texture feature of the vein image was achieved with the help of Gabor filter. The minimum distance classifier which employs the block matching strategy was used for the classification phase [5]. Kamaruddin et al. proposed a filter generation approach in deep learning for finger vein recognition. Many deep learning algorithms had been proposed like Googlenet, Alexnet, PCAnet, etc. The in-build feature in the Convolution Neural Network (CNN) does not consider the finger vein line characteristics. To overcome this limitation, the filter generation approach was introduced and the performance was analyzed with three popular finger vein image databases [6].
Liu et al. proposed a binary descriptor based finger vein recognition system which includes the Local Line Binary Pattern (LLBP) and Gabor features. In each pixel multi-directional pixel difference vectors are extracted for training the system. It was to improve the discriminating ability of the local features by learning the feature mapping. The finger vein image was represented as a histogram feature by pooling and grouping the binary codes [7]. Lu et al. proposed a deep convolution neural network for finger vein recognition using ImageNet. In AlexNet network, the CNN filters are visualized and analyzed from the first layer. The CNN filters are classified as five different labels based on outputs and appearances. The Convolution Neural Network Competitive Order (CNN-CO) was also applicable for all other kind of biometric applications [8].

**Finger Vein Based Testifying System:**
The complete block diagram of the finger Vein based testifying system is shown in Fig. 1.The finger Vein testifying system acquires the vein image from Infrared transmission based acquisition system and same was recorded using charge coupled device camera. The finger vein image was filtered using a Gabor filter and enhanced using Contrast Limited Adaptive Histogram Equalization algorithm.

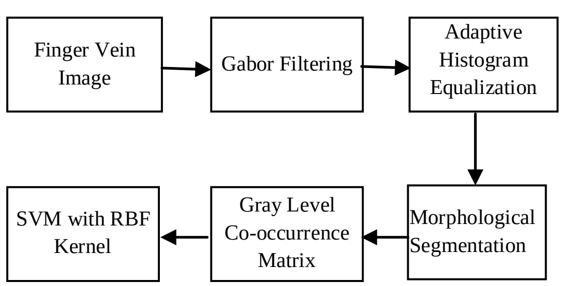


Fig: 1 Block diagram of the Finger Vein Based Testifying System.

The enhanced images are further segmented by using mathematical morphology - opening process. The texture feature values are extracted using Gray Level Co occurrence Matrix (GLCM) and finally got classified with Support Vector Machine with Radial Basis Function Kernel.

**Gabor Filtering:**

The Gabor filter is one of the types of wavelet which has an excellent frequency -domain and time-domain transform distinctiveness. The Gabor filters are designed by considering the parameters like direction, frequency, phase, and spatial position. The two dimensional Gabor filter sampled in a logarithmic behavior in frequency domain was used for filtering of finger vein images. The Gabor function represents the orthogonal directions of the vein image by means of real and imaginary component. A two dimensional Gabor function is given as follows.

$$g = \exp\left(-\frac{x'^2 + \gamma^2 x'^2}{2\sigma^2}\right)\exp\left(i\left(2\pi\frac{x'}{\lambda}+\varphi\right)\right) \quad \ldots (1)$$

$$g_{re} = \exp\left(-\frac{x'^2 + \gamma^2 x'^2}{2\sigma^2}\right)\cos\left(i\left(2\pi\frac{x'}{\lambda}+\varphi\right)\right) \quad \ldots (2)$$

Where

$$x' = x\cos\theta + y\sin\theta,$$
$$y' = -x\sin\theta + y\cos\theta \quad \ldots (3)$$

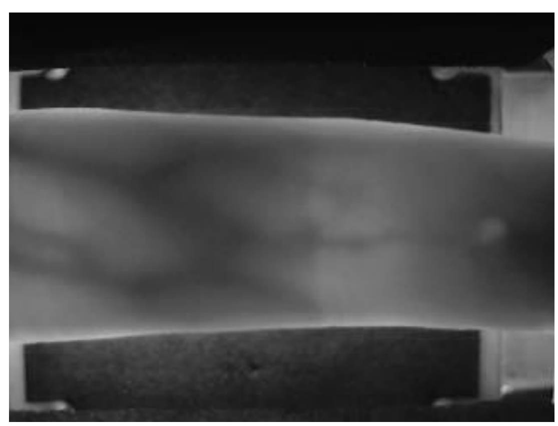

Fig 2: Input Finger Vein Image

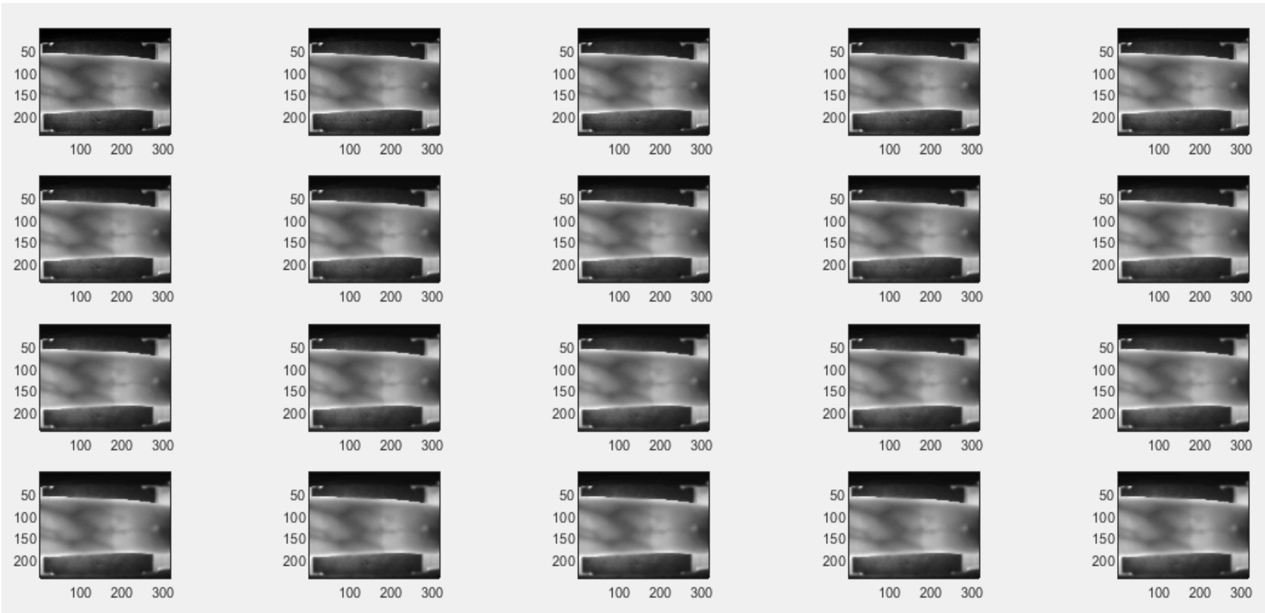


Fig 3: Gabor iterative results with different $\theta$ values.

The real part ($g_{re}$) of the Gabor function is used for finger vein recognition. In the function, the sinusoidal wavelength is $\lambda$. The frequency of sinusoidal is inversely proportional to the wavelength $\lambda$. In Gabor function $\theta$ is in normal orientation to the parallel stripes, $\varphi$ is the phase offset, Gaussian envelope describe by the standard deviation ($\sigma$) and the ellipticity of the Gabor function is specified by the spatial aspect ratio ($\gamma$).By considering the Gabor filter in four scales with eight directions and the range of $\theta$ and $\varphi$ is from 0 to 180 degrees. The default value of spatial aspect ratio ($\gamma$) is 1. The relationship between standard deviation and wavelength is expressed as below.

$$b = \log_2\left(\frac{\left(\frac{\sigma}{\lambda}+\left(\frac{1}{\pi}\right)\sqrt{\frac{\ln 2}{2}}\right)}{\left(\frac{\sigma}{\lambda}-\left(\frac{\sigma}{\lambda}\right)\sqrt{\frac{\ln 2}{2}}\right)}\right) \qquad \ldots (4)$$

Simplified formula:

$$\sigma = \left(\frac{1}{\pi}\right)\frac{2^b+1}{2^b-1}\sqrt{\frac{\ln 2}{2}} \qquad \ldots (5)$$

Where spatial frequency bandwidth of a linear Filter is considered as b and it is a half-response. The wavelength, orientation, and standard deviation are the major parameter that affects the Gabor filter waveform. The flows of the veins are along the direction of the finger growth. Based on the finger position, the veins are along two axes. The direction of the finger is analyzed by allotting the Gabor filter with $\theta$ value. For different values of $\theta$, the Region of Interest (ROI) of finger vein is filtered by using Gabor filter. The input finger vein image is shown in Fig.2 and the sequence of filtered images based on $\theta$ is shown in Fig.3.

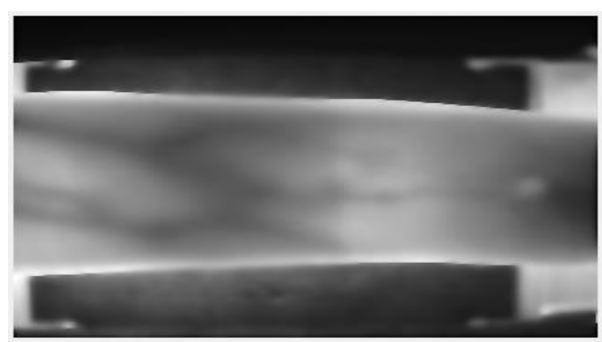

Fig 3: Output Image of Gabor filter

**Contrast Limited Adaptive Histogram Equalization**

Computer image processing techniques such as Adaptive Histogram Equalization are used in improving the image contrast which differs from ordinary histogram equalization in terms of lightness value redistribution. For improving the local contrast and to enhance the edge definitions of each region

Adaptive Histogram Equalization is suitable. It also over amplifies the noise at homogeneous regions of the image. This can be avoided by the use of Contrast Limited Adaptive Histogram Equalization.

Fig 4: Region of Interest

Fig 5: Enhanced Image

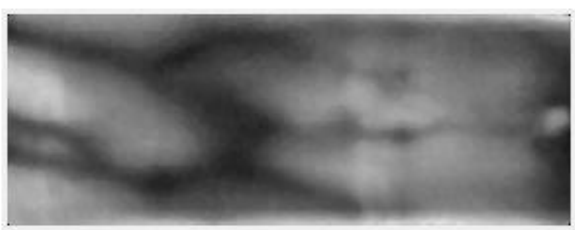

Fig 6: Finger Vein Filtered Image

The above Fig 4 shows the region of interest cropped from the Gabor filtered image. Fig 5 shows the enhance output image of contrast limited adaptive histogram equalization and Fig 6 shows the noise filtered image. The problem of noise amplification is reduced by a variant Adaptive Histogram Equalization termed as Contrast Limited Adaptive Histogram Equalization. The contrast amplification in surrounding area of a given pixel is expressed by the slope of transfer function which in turn is proportional to the slope of neigh CDF (cumulative distribution function).

**Morphological Segmentation:**

The acquired enhanced image after CLAHE is processed by morphological opening which includes; morphological erosion proceeded by morphological dilation in 12 direction. The output is smoothened and for frequency-domain conversion, top hat transformation was applied in 12 directions. The result is obtained by summing up the output of all the 12 directions. Finally, Gaussian filter of 5-pixel width is applied to get more smoothened image.

Step 1. Get the enhanced image $I_{enh}$ after CLAHE.

Step 2. Apply morphological opening $\alpha_o$ (morphological erosion $\varepsilon_o$ followed by morphological dilation $\delta_o$ on $I_{enh}$ in 12 directions).

$$\alpha_o = \delta_o(\varepsilon_o(M)) \qquad \text{... (6)}$$

Step 3. Smoothening the open image $I_o$

Step 4. Apply top hat transform on the smoothened image $I_s$ at 12 directions and get the result.

$$I_{top} = \sum_{i=1}^{12}(I_s - \alpha_{o_i}(I_{enh})) \qquad \text{... (7)}$$

| Features/ Image | Energy | Homogeneity | Kurtosis | Skewness |
|---|---|---|---|---|
| Image001 | 0.107812 | 0.759948 | 0.454695 | 0.946094 |
| Image002 | 0.10808 | 0.754780 | 0.462855 | 0.945960 |
| Image003 | 0.138613 | 0.681956 | 0.444770 | 0.930693 |
| Image004 | 0.110297 | 0.735031 | 0.485607 | 0.944852 |
| Image005 | 0.111908 | 0.745294 | 0.461256 | 0.944046 |
| Image006 | 0.116878 | 0.740677 | 0.446081 | 0.941561 |
| Image007 | 0.116641 | 0.739568 | 0.449089 | 0.941679 |
| Image008 | 0.118273 | 0.740258 | 0.440369 | 0.940864 |
| Image009 | 0.107772 | 0.736629 | 0.494643 | 0.946114 |
| Image010 | 0.105703 | 0.747958 | 0.486082 | 0.947148 |
| Image011 | 0.110024 | 0.731547 | 0.492236 | 0.944988 |
| Image012 | 0.086942 | 0.766206 | 0.548743 | 0.956529 |
| Image013 | 0.139002 | 0.718690 | 0.386195 | 0.930499 |
| Image014 | 0.120954 | 0.741990 | 0.424881 | 0.939523 |
| Image015 | 0.126144 | 0.738843 | 0.406747 | 0.936928 |
| Image016 | 0.112613 | 0.764735 | 0.421404 | 0.943693 |
| Image017 | 0.126814 | 0.737488 | 0.406192 | 0.936593 |
| Image018 | 0.098990 | 0.741784 | 0.527449 | 0.950505 |
| Image019 | 0.098681 | 0.787293 | 0.447127 | 0.950659 |
| Image020 | 0.132273 | 0.682547 | 0.468557 | 0.933864 |
| Image021 | 0.132998 | 0.675169 | 0.475255 | 0.933501 |
| Image022 | 0.104212 | 0.715206 | 0.540727 | 0.947894 |
| Image023 | 0.092032 | 0.790351 | 0.477457 | 0.953984 |
| Image024 | 0.135351 | 0.729289 | 0.382987 | 0.932325 |
| Image025 | 0.089427 | 0.791293 | 0.490090 | 0.955287 |

Step 5. Apply Gaussian filter with 5 pixels width of the output on $I_s$ to get more smoothened image.

$$I_G = Gaussian^{Width=5}_{\sigma=\frac{5}{4}}(I_{top}) \quad \ldots (8)$$

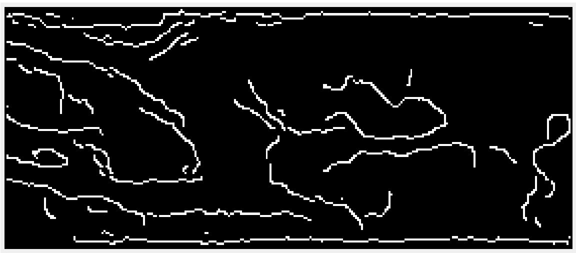

Fig 7: Finger Vein Edge Image

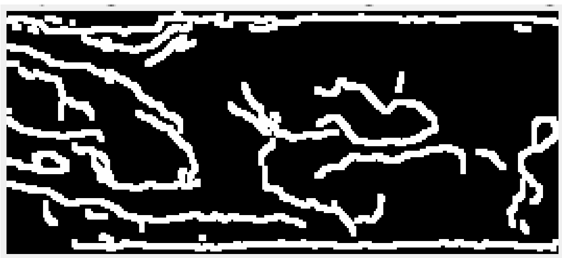

Fig 8: Final Vein Pattern

**SVM with RBF Kernel Classification:**

Radial basis function, a popular kernel method used in Support Vector Machine models, whose kernel values depends on the distance from the origin or from any other point. Table :1 shows the Comparison of Crossover Error Rate (CER) of the proposed system with the existing approaches as repeated line tracking, Wide line detector, Mean curvature, Maximum curvature point, Difference curvature combination, Region growth.

Table:1 Crossover Error Rate of various approaches:

| **Approaches** | **CER rate** |
|---|---|
| Repeated line tracking [24] | 12.85 |
| Wide line detector [25] | 07.62 |
| Mean curvature [26] | 04.20 |
| Maximum curvature point [27] | 08.30 |
| Difference curvature combination [28] | 07.90 |
| Region growth [29] | 05.71 |
| **Proposed Approach** | **03.51** |

**Gray Level Co-occurrence Matrix:**

The spatial relationships of pixels are considered for examining the texture based analysis stated by Gray Level Co occurrence matrix. The textures of an image are characterized by calculating the occurrence of pixel pairs with specific values and the specified spatial relationship occurring in an image [26]. GLCM is created and the statistical measures are extracted from this matrix. These statistics shows the details about the image texture. Energy, Homogeneity, Kurtosis, Skewness were the properties calculated and the following values have been shown in the Table: 1.

Table: 1 Feature values from properties of Gray Level Co-occurrence Matrix for 25 sample images

## Conclusion

The Support Vector Machine - Radial Basis Function Kernel with Gray Level Co occurrence Matrix features outperforms in finger vein authentication system. The noise free resultant from the Gabor filter supports morphological segmentation of vein images. Outperforming change in crossover error rate had been observed which articulates high drop over in CER rate from the existing approaches.

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