V.H.N.SENTHIKUMARA NADAR COLLEGE

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Virudhunagar

RESEARCH CENTRE IN COMPUTER SCIENCE

NOTIFICATION FOR Ph.D. PUBLIC VIVA-VOCE EXAMINATION

As per the regulations of Madurai Kamaraj University, Madurai, **Mrs. K.S. JEYALAKSHMI (Reg. No. P3184),** Assistant Professor, Department of Computer Science, N.M.S.S. Vellaichamy Nadar College, Madurai, will defend her Ph.D. thesis at a Public Viva-voce Examination through Video Conferencing mode using Google Meet Platform.

Title of the thesis	:	***"Fingerprint Image Recognition using Neural Network with Haralick Features and Enhanced Algorithms for Image Enhancement, Core Point Detection and Classification"***
Date & Time	:	**December 18, 2020 (Friday)** **11.00 A.M**
Venue	:	**Research Centre in Computer Science** **V.H.N.Senthikumara Nadar College**
Video Conference Platform	:	**Google Meet**
Meeting ID	:	meet.google.com/isa-vmnp-itj
External Examiner	:	**Prof. Dr.M. SUNDARESAN** Head, Department of Information Technology Bharathiar University, Coimbatore.

The synopsis of the thesis is available in the college website (www.vhnsnc.edu.in) and a copy of the thesis is available in the Research Centre in Computer Science for reference. **Faculty members, Research Scholars, Experts, Students and others who are interested in the subject are invited to attend the Ph.D Public Viva-voce Examination** and take part in the discussion.

8/12/20

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Fingerprint Image Recognition Using Neural Network with Haralick Features and Enhanced Algorithms for Image Enhancement, Core Point Detection and Classification

SYNOPSIS OF THE THESIS SUBMITTED TO
MADURAI KAMARAJ UNIVERSITY
IN PARTIAL FULFILMENT OF THE REQUIREMENTS
FOR THE AWARD OF THE DEGREE OF

DOCTOR OF PHILOSOPHY IN COMPUTER SCIENCE

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JULY 2019

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SYNOPSIS

Biometric is the technology to identify a person based on some aspect of their biology. Fingerprint recognition is the first biometric technology used for identification and authentication. Among various biometrics namely signature, fingerprint, voice, iris and gait, fingerprint is widely accepted and used because of its uniqueness, ease of use, durability and affordability. Fingerprints are the impressions on glass like smoothed surfaces made by papillary ridges on the ends of human fingers. Fingerprint image consists of ridges and valleys. Ridges are the raised portion of epidermis found on the finger whereas valleys are the areas between two adjacent ridges. Ridges and valleys in the fingerprint image forms some patterns as left loop, right loop, whorl, arch and tented arch. Recognition of fingerprint may be based on minutiae (Espinosa-Duro *et al.,* 2002), features (Dale *et al.,* 2007; Yang, 2011) or correlation (Lindoso *et al.,* (2007). The patterns in the fingerprints are classified on the basis of positions of singular points. Core and delta points are called as singular points. Core point is the point of an inner-most ridge that has highest curvature and a delta point is a place where two ridges diverge. Fingerprint orientation image is a map that represents orientation of the flow of ridges and is used in fingerprint image enhancement, classification and recognition. Also it is used in identifying singular points.

An image is preprocessed for uniformity, identifying region of interest, noise suppression or for enhancing features to improve accuracy, and minimizing time complexity for image related problems. Generally preprocessing methods used in image processing are for resizing, cropping, binarizing, segmenting, normalizing and filtering the images.

Noisy background is suppressed after segment the image during preprocessing. Segmentation is the process of separating foreground from background. Yin *et al.,* (2005) have proposed a novel segmentation based on quadric surface model that uses mean, variance and coherence of each pixel. Xiao-Dong *et al.,* (2006) have introduced self-adaptive local threshold for segmentation method. Ren *et al.,* (2008) have implemented a linear hybrid classifier to segment the fingerprints using block-wise classifier and pixel-wise classifier. Features are the unique signatures to represent an object. Images defined by features are the dimensionally reduced representation. These features are very essential to differentiate one object from another. Fingerprint image features are singular points as the global features, minutiae as level-2 features and sweat pores as level-3 features. Ratha *et al.,* (1995) have proposed a novel structural features extraction method that uses orientation for designing adaptive filters to enhance the ridge features and uses waveform projection based method for segmenting the fingerprint image. They have also used morphological operators for smoothing the ridge features and removed spurious features in the postprocessing phase. The extracted structural features are evaluated by computing a goodness index.

Core point is a reference point used to identify uniqueness among different samples. Core point detection is used to recognize the fingerprint even though there are different poses of same finger (Jiang *et al.,* 2004). Singular points also called as level 1 features of a fingerprint (core and delta point) are unique landmarks of fingerprint. They are used as reference points for fingerprint matching and classification (Karu and Anil, 1996; Zhang and Hong, 2004). The core point has played an important role in most fingerprint identification systems (Maltoni *et al.,* 2009) and is widely used in fingerprint classification (Jain *et al.,* 1999; Wang and Yangsheng 2004) and fingerprint matching (Maio and Davide, 1997; Jain *et al.,* 1997; Jain *et al.,* 2000). The typical core point detection methods are based on Poincare Index (PI) analysis.

In automatic fingerprint identification system (AFIS), large number of fingerprints are captured and stored in a database for future reference. Whenever authentication is needed, the scanned fingerprints are compared with the enrolled fingerprints. It takes more time if the comparisons are made against the entire enrolled fingerprint images. So, the large database is split into a subset of fingerprints that are having similar patterns like left loop, right loop, whorl, arch or tented arch. This splitting of similar fingerprint patterns into a single subset is called fingerprint classification. This helps for fast recognition in AFIS. After the classification process, type of the input fingerprint is identified and is compared with images in the class group of the database for exact matching.

While using the fingerprint image for authentication, one have to do preprocessing for preparing the input in a convenient format for extracting the required features, enhancing the image for better visualization and classifying the image into smaller subgroups of similar patterns and recognizing the person. Features like orientation image, singular points and number of core points are extracted in the feature extraction phase. Jain *et al.,* (1999) have used a novel feature vector called FingerCode which is the collection of all the features defined for each sector in each filtered image and have been classified based on a two-stage classifier which uses a K-nearest neighbor classifier in the first stage and a set of neural networks in the second stage. Zhang and Hong (2004) have proposed fingerprint classification based on both singularities and traced pseudoridge analysis. Park and Haesun (2005) have proposed a fingerprint classification method based on discrete Fourier transform (DFT) and nonlinear discriminant analysis (NDA) where DFT and directional filters are used to extract directional image and NDA is used to extract discriminant features and to reduce the dimensions of the extracted features. Wang and Mo (2007) have proposed a fingerprint classification method using the location of singular points where singular points are detected based on the distribution of Gaussian–Hermite moments. Li *et al.,* (2008) have proposed an algorithm for fingerprint classification based on the interactive validation of singular points and the constrained nonlinear orientation model. Liu (2010) has presented a fingerprint classification algorithm using adaboost learning method to model multiple types of singularity features and to design a classifier for classification. Cao *et al.,* (2013) have presented a regularized orientation diffusion model for extracting orientation of the fingerprint and a hierarchical classifier for fingerprint classification. A rule-based fingerprint classification method is proposed by Guo *et al.,* (2014) wherein two features namely types of singular points and number of each type of points are used to distinguish different fingerprints. Even though more and more fingerprint classification methods are proposed in the literatures, some improvement is needed in terms of time and accuracy.

In the hectic world, poor quality (wet or dry) images are captured without any care for the automatic personal identification. These poor quality fingerprint images lead to degrade the accuracy of Automatic fingerprint identification system (AFIS). Its accuracy can be increased if an enhancement process is used prior to the feature extraction process. Some may have scars in the fingers that may lead to ridge discontinuities. These degraded low quality fingerprint images have to be enhanced for better visualization of ridge-valley structure. This enhancement is done by filtering techniques. It is also considered as one of the preprocessing task that enhances the fingerprint image features orientation and minutiae.

Hong *et al.,* (1998) have used Gabor filter as a low pass filter to eliminate noise and retain features of fingerprint but produced blocking artifacts in the enhanced fingerprint image. Yang *et al.,* (2003) have developed the modified Gabor filter using the traditional Gabor filter which preserves fingerprint image structure and achieves image enhancement consistency than traditional Gabor filter. Blotta and Emilce (2004) have used differential hysteresis processing for enhancing the defective fingerprint images. Zhang *et al.,* (2004) have proposed a fingerprint enhancement using wavelet transform combined with Gabor filter. Cheng and Jie (2004) have introduced the scale space theory in the computer vision to enhance the fingerprint. Anisotropic filter combined with directional median filter was used by Wu *et al.,* (2004) for fingerprint image enhancement. Çavuşoğlu and Salih (2008) have proposed a fingerprint enhancement algorithm that uses the direction for designing a mask of parabolic coefficients and leads to filtering fast. Wang *et al.,* (2008) have proposed an algorithm that enhances fingerprints using log-Gabor filter. Ye *et al.,* (2012) have used 2-D empirical mode decomposition in their proposed fingerprint enhancement algorithm. Even though lots of algorithms were proposed for fingerprint image enhancement, improvement in time and accuracy are still needed.

In general, fingerprint recognition and classification are comprised of a feature extractor and classifier. The feature extractor gives fingerprint descriptors and is used in the classifier for recognizing or classifying the fingerprints. Features can be extracted through Principle Component Analysis (PCA), wavelet decomposer and analysis of statistical measures. Classifier may be a neural network, support vector machine (SVM), K-nearest neighbors (K-NN) classifier or self-organizing map(SOM). Fingerprint recognition is the process of identifying the identity of a person based on comparison of two fingerprints.

Luo *et al.,* (2000) have proposed fingerprint verification system using the modified version of minutiae matching algorithm of Jain *et al.,*. Jea *et al.,* (2005) have presented a minutia-based partial fingerprint recognition system that uses a fully connected neural network with a two-hidden-layers and is trained to generate the similarity score based on minutiae matched in the overlapping areas. Gu *et al.,* (2006) have proposed a fingerprint recognition by combining the decisions of the matchers based on the global structure (orientation field) and the local cue (minutiae). Ito *et al.,* (2006) have proposed a fingerprint recognition by combining phase-based image matching and feature-based matching for verifying low-quality difficult fingerprints. Yang *et al.,* (2006) have proposed fingerprint matching algorithm with the preprocessing task as removal of background and noise, image enhancement through Discrete Wavelet Transform, and reference point detection. They have constructed seven invariant moment features for learning vector quantization neural network. Wan and Jie (2006) have proposed a polynomial model to approximate the density map of fingerprints for fingerprint recognition. Hasegawa *et al.,* (2006) have presented a fingerprint identification system using neural network with the preprocessing methods fast Fourier transform (FFT) and inverse FFT (IFFT). Yuan *et al.,* (2007) have proposed fingerprint recognition by minutiae matching algorithm with image enhancement as preprocessing. Zhao and Xiaoou (2007) have proposed preprocessing steps that remove spurious minutiae like dots, lakes, bridges and spurs from the fingerprint skeleton. Qader *et al.,* (2007) have proposed a fingerprint recognition using Zernike moment invariant as shape descriptor. Zhao *et al.,* (2009) have proposed a fingerprint recognition in which similarity score is calculated based on the pore matching results. Cappelli *et al.,* (2010) have proposed a new representation called, a minutia cylinder-Code and matching technique for fingerprint recognition for light architectures such as a smart card or a system-on-a-chip. Pornpanomchai *et al.,* (2010) have proposed a fingerprint recognition system using Euclidean distance and they have followed sharpness adjustment process and core point detection in the preprocessing. Liu *et al.,* (2011) have proposed a fingerprint recognition system using pore matching by adopting coarse-to-fine strategy where a tangent distance and sparse representation based pores matching are used in coarse level and a weighted RANdom SAmple Consensus(RANSAC) algorithm is used in fine level. Win *et al.,* (2011) have proposed a method for recognizing low quality fingerprint image using textural features. They have used estimation of orientation image and Gabor filtering as preprocessing. Bartunek *et al.,* (2012) have proposed pre-processing method based on a nonlinear dynamic range adjustment to recognize fingerprints. Yang *et al.,* (2013) have presented a fingerprint matching system with preprocessing and they have used the classifiers extreme learning machine (ELM) and regularized ELM. Kumar *et al.,* (2013) have presented a fingerprint matching system using feedforward neural network. Local directional patterns are used in training the network. They have used normalization and segmentation as preprocessing tasks in the system. In general, time consumption in the preprocessing task slow down the fingerprint recognition process while handling voluminous fingerprint database (Li *et al.,* 2012; Tselios *et al.,*; El-Feghi *et al.,* 2011). Hence, efficient recognition without preprocessing is a need of the hour.

One dimensional histogram is the simplest statistic measure but it is not a good texture measure (Mirzapour *et al.,* 2013). Two-dimensional histogram introduced by Abutaleb *et al.,* (1989) consumes more time. GLCM overcomes the computational cost problem occur in two-dimensional histogram and also it overcomes the weakness of one dimensional histogram in the texture analysis. In spatial domain, statistical measures are computed for the conditional joint probabilities matrix called gray level co-occurrence matrix to generate second order texture features named Haralick features. In general, these statistics identify some characteristics of the structural texture of the input image by means of the arrangement of probabilities within a GLCM indexed on (i, j). The spatial window of interest for computing GLCM has two parameters: inter-pixel distance (d) and orientation (θ) (Haralick *et al.,* 1979). The GLCM features are mostly used in texture based image analysis applications (Zaim *et al.,* 2006; Hazra *et al.,* 2011; Ribaric *et al.,* 2012; Jafarpour *et al.,* 2012).

GLCM is in the form of square matrix with an order N $\times$ N where N is the number of gray levels. The value in the position (i,j) of $GLCM_{d,\theta}$ represents number of occurrences of pixels with the gray levels j at the distance d and with gray level i at the direction θ. The spatial relationship between reference pixel and its neighbourhood is defined by GLCM. The spatial relationship is number of rows between reference pixel and its neighbourhood, and number of columns between reference pixel and its neighbourhood. Different statistics measures calculated from GLCM are mean$_x$,mean$_y$, σ_x, σ_y, homogeneity, inertia, local homogeneity, entropy, energy, contrast, correlation, variance, sum of average, sum of entropy, difference of entropy, shade and prominence. Mean and standard deviation are first order statistics concerned with properties of individual pixels whereas second order statistics are dealt for the spatial interdependency or co-occurrence of two pixels at specific relative positions. More number of fingerprint recognition systems are proposed in the literatures compete with others by its accuracy, speed, novelty, methodology, memory, and complexity.

GLCM becomes wavelet co-occurrence matrix in wavelet domain. Compute the wavelet co-occurrence matrices at a distance d=1 and orientation θ at $0°$, $45°$, $90°$ and $135°$ for the approximation image obtained through wavelet transform. The computed wavelet co-occurrence matrices are the second order statistical representation of the input fingerprint image. Among 16 features, four wavelet co-occurrence features namely contrast, correlation, energy and homogeneity are selected for recognition and these can be estimated from the wavelets co-occurrence matrix.

In this thesis, enhanced algorithms are proposed for core point detection, image enhancement, fingerprint image classification, and recognition using Haralick features. Shape analysis is performed on binary candidate region image to identify the location of core point. Singular point locations are used as features for rule based fingerprint classification. Fingerprint orientation is used to design steerable filter and is applied on the approximation image obtained by wavelet decomposition of the fingerprint image. Haralick features are used for fingerprint recognition in spatial and wavelet domain. These leads to fast fingerprint recognition without compromising on recognition accuracy. The content of the dissertation is described chapterwise as follows.

In chapter 2, optimal core point is detected by analyzing the binary candidate region image (BCRI). ROI for core point identification is the foreground of the fingerprint image which contains the features singular points, minutiae and sweat pores. Segmentation is used to find ROI by eliminating background noise details. In the proposed method, segmentation is done by generating mask with morphological operators. The essential orientation feature to locate core point in a segmented fingerprint image is estimated through muti-scale PCA. The estimated orientation is divided into homogeneous zones and constructed the $BCRI_U$ and $BCRI_L$ to do shape analysis in order to locate upper and lower core point respectively. The upper core point is identified from $BCRI_U$. It is the bottommost block of each connected candidate region of $BCRI_U$ with 8 neighboring blocks having orientation values in non-decreasing order from 0 to π in clockwise direction and also at least four of its neighboring blocks with unique homogeneous zones. Similarly lower core point is also detected using $BCRI_L$ by considering topmost of each connected candidate region instead of bottommost of each connected candidate region. The proposed work detects more accurate core point location in less time but consumes more time for extracting the feature orientation.

In chapter 3, the fingerprint image enhancement using steerable filter in wavelet Domain is presented. For enhancing the fingerprint image, the proposed work uses the orientation image. The orientation image is to be divided into homogeneous zones in order to retain originality and to avoid artifacts in the enhanced image. Single level wavelet decomposition is applied on the fingerprint image and only approximation image is considered for further processing. Approximation image is divided into smaller local blocks and steerable filter is constructed using basis filters . Enhanced image is obtained by convolving the local block with steerable filter and its orientation. The proposed method has no FMR and no EMR whereas the image without enhancement results with FMR and EMR. Similarly better performance evaluation is found for the enhanced image.

In chapter 4, fingerprint classification system based on singular points and orientation information is presented. For fingerprint classification, it uses the number of core points, their locations and the orientation image. The proposed work uses rule based classification and classifies even the partial fingerprints. The proposed work is also able to classify the cross-referenced fingerprints. The rule classifies the fingerprint as *arch* if the core point is not detected, classifies as *whorl* if there are two core points (upper and lower core point). Delta point location is used only for distinguishing left loop, right loop and tented arch from the whorl type when one core point is detected. If no delta is detected, then by considering five rows of blocks below the core point location, the blocks having 45° (RC) and 135° (LC) are counted. If there are more RC than LC then the fingerprint is identified as *right loop* otherwise *leftloop*. If two delta points are detected then the fingerprint is classified as *whorl*. If only one delta point is detected and singular points are aligned vertically then the fingerprint is classified as *tented arch*. If delta point is one, and is left to core point and the distance between singular points is less than 2 horizontally and less than 3 vertically then the fingerprint is classified its primary type as *tented* and secondary type as *right loop*, otherwise *right loop*. If delta point is one, and is right to core point and the distance between singular points is less than 2 horizontally and less than 3 vertically then the fingerprint is classified its primary type as *tented* and secondary type as *left loop*, otherwise *left loop*. The proposed work gives high accuracy without rejection and classifies more accurately the ambiguous fingerprint images into its primary as well as secondary class.

In chapter 5, fingerprint recognition using neural network with wavelet co-occurrence features is presented. The proposed work aims to recognize fingerprint without preprocessing but with less time and without compromising on accuracy. The four Haralick features namely contrast, correlation, energy, and homogeneity are extracted from wavelet co-occurrence matrix of approximation image after the wavelet decomposition process. The extracted features are used in feedforward neural network for recognizing fingerprints. The Levenberg-Marquardt algorithm is used to train the network. Better recognition rate is obtained in the proposed method with less time.

In chapter 6, fingerprint recognition using neural network with Haralick features is presented. Fingerprint is recognized through feedforward neural network with only four Haralick features namely contrast, correlation, energy, and homogeneity extracted from gray level co-occurrence matrix of four different directions. Generalized delta rule is used to train the network. The proposed method produces better recognition rate in less time. The concluding remarks and future enhancements constitute chapter 7. The proposed methods are tested on public fingerprint databases NIST Special database 4 and set B of FVC 2000, FVC 2002, FVC 2004 databases. Results of every method are comparably better than the related works in the literature. Fingerprints are recognized with good accuracy in less time. The proposed methods are implemented using MATLAB 2013a on Intel(R) Xeon(R) CPU E5-16070 @ 3.00 GHz for all databases.

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