An Intelligence Based Approach for Palmprint Recognition using Ant Colony Optimization

Merlin Linda George, Themozhi Govindarajan and Sudheer Reddy Bandi

1Department of Information and Communication Engineering
Anna University,
Chennai, India.
merlin.linda@gmail.com

2Department of Electronics and Communication Engineering
Tagore Engineering College,
Chennai, India.
gthemozhivijayakumar@gmail.com

3Department of Computer Science and Engineering,
Tagore Engineering College,
Chennai, India.
bsudheer115@gmail.com

Abstract

Palmprint is an essential biometric feature used in various applications like banks, criminal, forensic and commercial applications. A palmprint image contains various distinctive traits for reliable authentication when compared to other biometrics. In this paper, a new adaptive technology known as Ant Colony Optimization based edge detection, popularly known as Ant Colony System (ACS) is used. For preprocessing, gabor filter based texture analysis is applied to extract the features from palm images. Ant Colony Optimization (ACO) is a novel and heuristic discipline rooted from the movement of ants in ant colonies to search food. Ant Colony Optimization is a stochastic methodology used in finding solutions for many computational problems. The main objective of edge detection is to identify changes in the intensity of the image. In the first stage, ACS is applied for detecting edges which creates matrix pheromone that shows information of each edge available in pixel based on ant movements. In the second stage, an edge detected image is filtered with a set of gabor filter at multiple scales and orientation to extract texture features. The features are
classified as multiclass Support Vector Machine (SVM) classifier. Results are obtained and analyzed. Our experimental results demonstrate the classifier has high accuracy with fewer feature dataset. The expenditure of this algorithm is less when compared with other conventional or traditional edge detection approaches.

**Keywords:** Palmprint Recognition, Texture, Edge detection, Gabor filter, Biometrics, Pheromone, Ant Colony Optimization.
1. Introduction

Biometrics is increasingly becoming more and more popular in the real world entity. The advances in biometric technology have led to rapid growth in biometric authentication. Biometric helps to authenticate or identify the identity of an individual based on specific palmprint recognition [1]. With the encroachment of computer technology, various Human-Computer Interaction (HCI) techniques came into existence. Biometric authentication is defined as the process to identify an individual using unique physical or behavioral attributes. Table 1 compares the requirements of various biometric characteristics.

Biometric authentication techniques are broadly classified into three categories: token based, knowledge-based, physiological or behavioral characteristics. The token-based approach consists of identity cards, passport, and other cards. These tokens can be lost or easily stolen. In knowledge-based approach, passwords should be remembered which is a difficult task for all human beings [2]. To overcome all these problems various physiological characteristics of human beings like iris, fingerprint, palmprint, voiceprint, hand geometry, and DNA are considered for biometric authentication systems [3,4]. Iris and retina give high recognition results but capturing devices cost are much more. Also, it is not possible to take iris recognition from color blinded people and blind people. The social acceptability and complexity are more in taking the iris features. Fingerprint identification is intrusive since it is used for criminal identification and also it requires high-resolution images. Fingerprint recognition varies with age since the size of the finger increases; we cannot identify the correct recognition if the fingers are dry, dirty. Similarly, if the person has various skin problems and if there are any injuries. Many of these drawbacks can be overcome by using palmprint biometric system. Palm lines are also known as ‘lines of fate’. The palm lines are formed in the budding or embryonic phase of the baby which is in the third month of fetal development inside mother’s womb. The baby folds the palm for long period. The skin is so sensitive at this stage the lines are formed. Palmprint has various main features like principal lines, wrinkles, and creases as described in, [5]. Palmprint image is mainly divided into three regions like finger-root region, an inner region and root region as shown in Fig. 1.

![Fig. 1. Formation of palmprint regions and lines](image-url)
TABLE I. THE JUDGMENT OF VARIOUS CHARACTERISTICS OF BIOMETRICS

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Finger</th>
<th>Iris</th>
<th>Signature</th>
<th>Voice</th>
<th>Palmprint</th>
<th>Face</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceptance</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>Medium</td>
</tr>
<tr>
<td>Accuracy</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Medium/High</td>
<td>High</td>
</tr>
<tr>
<td>Cost</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Circumvention</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Easiness of use</td>
<td>High</td>
<td>Low</td>
<td>High</td>
<td>High</td>
<td>High</td>
<td>Medium</td>
</tr>
</tbody>
</table>

Palmprint identification is divided into two categories: off-line and online. In online palmprint verification system, palm images are captured directly from the sensor [6]. The images are sent to the computer for real-time processing. Presently the focus is on off-line palmprint authentication system where palm images are inked and digitized through an image scanner. Palmprint authentication system is used in various fields of intelligence like forensic, banks, criminal, military applications, education institutions and attendance etc.

Palmprint is a unique and reliable biometric characteristic with high usability. Palmprint images are distinctive for reliable human identification, which makes a competitive topic in biometric research. Relatively biometric feature has several advantages compared with other currently available features [1,2,6]. Palmprint contains more information than a fingerprint, so they are more distinctive; palmprint capture devices are much cheaper than iris devices; palmprint can be extracted from low-resolution images. Highly accurate biometrics system can be built by combining all features of palm geometry, ridge, valley features and principle lines, etc. This makes palmprint recognition much more challenging than another traditional method of identification.

Palm vein information can symbolize the liveness of an object [7]. It can be difficult to be modified as an internal feature. Similarly, it simulates using a fake palm. Because of these features, hand and palm vein seems a better biometric technique compared with other biometrics like fingerprint and face. Furthermore, palm vein is considered as the inner features of the body, it can’t be fabricated, palm vein recognition is contactless and its characteristics are long-lasting.

The paper is organized as follows: in section 2, an overview of palmprint and various preliminaries are presented. Section 3 briefly describes Ant colony optimization and its functions based on Ant colony system. Feature extraction using gabor filter is explained in section 4. In section 5 summary of multiclass SVM approaches and experimental results are analyzed. Finally, the conclusion
is given in section 6.

2. Related Work

Researchers on palmprint recognition started on a 14-th century in China were merchants used palm lines to distinguish customers. Back to 500 B.C, fingerprints were used by Babylonia to record business transactions on clay tables. The state-of-the-art palmprint recognition algorithm has been presented in the literature for identification of our work in biometrics.

Extraction of feature vector based on wavelet coefficients for palmprint biometric system has been proposed [8]. Based on palm geometry square shaped Region of Interest (ROI) is extracted from the aligned image. Further processing is done on the coefficients obtained from Discrete Wavelet Transform (DWT) to generate the feature vector. In palmprint identification system [9], a particular person's biometric template is compared against all images in the database to identify the person. The matching procedure in large database degrades the performance of the biometric system. It consists of three stages feature extraction, hashing generation and querying. 2D-Log gabor, Phase Congruency, and Haralick feature methods are used for identifying palmprint feature recognition.

An efficient palmprint alignment refinement method to extract the principal lines from palmprint image has been presented in [10]. To estimate the translation and rotation parameters between two images iterative closest point has been applied. The estimated parameters are then used to refine the alignment of palmprint feature maps for a more accurate palmprint matching. Results show that refinement method greatly improves the palmprint recognition accuracy and works in real time. A novel Feature-Similarity Indexing (FSIM) algorithm is presented in [11]. It is used to generate the matching score between the original image in the database and the input test image. Feature Similarity index for full reference Image Quality Assurance (IQA) is proposed. Based on the fact that Human Visual System (HVS) understands an image mainly according to its low-level features. To find edge detection use Canny and Prewitt FSIM methods, followed by log gabor filter. Results are generated with an accuracy of 97.3%

The palmprint segmentation method to extract the central part of palmprint features based on hybrid approach has been proposed in [12]. A hybrid approach to palmprint recognition system integrates Contourlet Wavelet Transform (CWT) and Principal Component Analysis (PCA). The Support Vector Machine (SVM) is used as a feature classifier to improve the recognition performance. CWT with AdaBoost classifier for palmprint classification [13] is used where the error rate is very low. A palmprint based identification system [14] using the textual information, employs different wavelet transforms. The wavelets used for the analysis are Bi-orthogonal, Symlet, and Discrete Meyer. The transforms employed have been analyzed for their individual as well as combined performances at feature level.227% and 94.718% respectively.
Multispectral palmprint fusion was proposed in [15]. It uses intra-model fusion environment to integrate multiple raw palm images at a low level. Fusion of palmprint is performed by wavelet transform. Haar wavelet is used for extracting wavelet coefficients. The wavelet fusion method is used to combine the wavelet coefficient information obtained from multispectral images. Fused image is converted to 2D gabor wavelet at high dimensional space. To reduce high dimensionality, ACO is applied. The reduced feature set is trained with SVM classifier. Palmprint recognition using score-level fusion was proposed in [16]. It authenticates individuals based on multi-scale and multi-resolution palmprint recognition. First extract the palmprint feature based on Non-Subsampled Contour Transform (NSCT), and store using a hash table. Then the scores are combined using score level fusion method. This method use SUM and MAX operators. A comparison of palmprint identification techniques based on fractional coefficients has been presented in [17]. The transforms are namely Cosine, Haar, and Kekre. It is used to reduce the feature vector size of palmprint images by selecting low-frequency coefficients in transformed edge images.

Texture-based palmprint recognition system has been proposed in [18], for maintaining employee entry record. The images are extracted by using simple texture methods. The training set is prepared with the help of K number of samples per user, where K varies from 1 to 4. Results are compared with Fast Fourier Transformation (FFT), Discrete Cosine Transformation (DCT), and Discrete Wavelet Transformation (DWT). These methods are checked against remaining images in the recognition mode. The texture patterns are spread over entire palmprint image those are used for feature extraction. A comparative study of Region of Interest (ROI) and Principal Component Analysis (PCA) has been proposed in [19]. The region of Interest is employed to reduce the error caused due to translation and rotation. To extract ROI of palm image, define a coordinate system based on which the input images are aligned for matching and verification. For obtaining palmprint feature vector and matching is done by Hausdorff Distance (HD) method. PCA is called appearance-based methods, which operate directly on an image-based representation. The recognition rates are unexpectedly improved when compared to the classic approaches.

An efficient approach for automatic palmprint classification based on principle lines was proposed in [20]. It consists of a lifeline, a headline, and a heart line. However, several thin and weak palm lines, such as wrinkles, might be too vague for detection. Palm lines and texture are two kinds of local distinctive and stable features for low-resolution palmprint authentication. Fisher palms based palmprint recognition has been presented in [21]. It uses second order Gaussian derivatives to detect the location of the line. Hierarchical palmprint recognition based on complex wavelet texture feature has been presented in [22]. It generates a probability distribution template of major line. Then dual-tree complex wavelet is applied onto palmprint image to obtain texture feature. With the help of hierarchical matching, strategy features are applied for recognition.
Palmprint recognition based on Discrete Cosine Transform (DCT) was proposed in [23]. It extracts the linear discriminative features by an improved Fisherface method and performs the classification by the nearest neighbor classifier. It can significantly improve the recognition rates for palmprint data and effectively reduce the dimension of feature space. Palmprint recognition based on Translation Invariant Zernike Moments (TIZM) and Modular Neural Network (MNN) has been proposed in [24,25]. TIZM and the extracted features are classified using multilayer perceptrons. Complex Zernike moments are constructed using a set of complex polynomials which form a complete orthogonal basis.

3. Ant colony optimization

Edge detection is normally defined as a process of identifying the pixels in an image where sharp changes in intensity occur. Edge detection is very important in acquiring the basic information of an image. It plays an imperative role in image processing and human-computer interaction as a preprocessing technique to extract the features of the image. Many conventional or traditional edge detection approaches like Roberts, Prewitt, and Canny have many drawbacks. These approaches are computationally expensive since operations are performed on each individual pixel of an image. Many traditional methods output the broken edges of an image and also the algorithms are not adaptable for distributed systems. The above drawbacks can be overcome by using Ant Colony System which is ACO based edge detection algorithm and also the algorithm can be parallelized so that it is adapted for distributed systems.

As represented in the block diagram Fig. 2, in training phase the Region of Interest (ROI) palmprint images are taken for preprocessing using ACO based image edge detection. In the second step, the preprocessed images are filtered using 2D gabor filter to extract the texture features. The same procedure is followed in the testing phase to extract the features from the palmprint images. In the final stage, multiclass SVM approaches are applied to recognize the palm lines of the individuals.

![Block diagram for palmprint recognition](image-url)
ACO is a meta-heuristic technique for optimization of many combinatorial hard problems introduced by Marco Dorigo in 1992 in his Ph.D. thesis. Initially, the algorithm was applied for solving the problems of graph theory especially to solve traveling salesman problem. In the later stages, ACO was applied in various fields of research like network analysis for estimating the topology of the networks. In image processing techniques like image segmentation, preprocessing, processor scheduling in allocating the tasks for various processors, solving various optimization problems like knapsack problem and minimum weight vertex cover problem. These heuristic techniques can be used to solve various real-time applications like water resources system analysis, traffic signal timings, and train schedules. ACO is a nature stimulated optimization algorithm that is motivated by the natural foraging behavior of ant species. The strategy of ACO is “exploration and exploitation” in which the exploration is a procedure where ants find the promising path in the search space. Exploitation is the process of usage of the best possible solution by the other members of the ant colony to arrive at the optimal solution.

The work of ACO is described as follows: (1) Ants normally move from their nest (N) to the food source (F) randomly by leaving the pheromone trails in their path and return to their nest after taking the food. During the process, the shorter path is reinforced by leaving more pheromone trails. (2) Among all the possible ways the ants normally follow the shorter path. (3) After some time pheromone will be evaporated making the shorter path available for the ants whereas the longer path will not be available. This behavior of ACO is demonstrated in Fig. 3. The advantage of evaporation of pheromone is that the shorter path will be followed by the members of ant colony leaving the longer path. One ant follows the shorter path and leads the other ant colony members to follow their path with the help of pheromone trails. This positive feedback mechanism is adopted in ant colony optimization.

![Fig. 3. The behavior of an ant colony](image-url)
There are various variations of ant colony optimization but the major versions are (i) Ant System, (ii) Ant Colony System (ACS) and (iii) Max-Min Ant System. Regarding edge detection, there are two techniques based on ACO. They are Ant System (AS) based edge detection proposed by Nezamabadi et al [26] and the second algorithm is ACS based edge detection introduced by Jing Tian et al [27]. In this study, we apply ant colony system based edge detection for the palmprint images to extract the edges which will be studied in detail in the next section. As described in, [28] there are lots of essential differences between Ant System based edge detection and Ant Colony System based edge detection. ACS uses a pseudo-random proportional rule which reinforces the exploitation of the search space. In ACS pheromone evaporation and deposit are done only on edges belonging to the best so far tour. Third, each time an ant uses an edge to move from node to another, it removes some amount of pheromone from that adjoin to increase the exploration of other edges. This process is called as local pheromone update which is performed only in ACS.

In this context, ACS algorithm is applied for 2D palmprint image of size M×N where each pixel is considered as a node which serves as food for ants. Totally k ants are applied to find the optimal solution in the search space X to construct a pheromone matrix in which each entry represents the edge information. The proposed technique starts from the initialization process to decision phase which has construction, update process in between and runs up to N iterations. The summary of ACO can be given as follows:

**Initialization Process**

In this process, palmprint image (I) of size 128×128 is taken as an input which works as a solution space X for the ants. Consider k = 40 numbers of ants are moved over the image so that every pixel of the image is covered by the ant. The preliminary value of each component of the pheromone matrix is taken as $t_{init} = 0.0001$. In our adaptive technique, a heuristic matrix $\eta_{i,j}$ is evaluated based on the local statistics of the image which depends on the clique. Clique is defined as the groups of ants connected or taken together. In our problem 8-connectivity is taken as clique mode. The local information of the pixel at the position $(i, j)$ is given by Eq. (1)

$$\eta_{i,j} = \frac{v_c(t_{i,j})}{v_{max}}$$

Where

$$V_c(t_{i,j}) = f \left( |t_{i-1,j-1} - t_{i+1,j+1}| + |t_{i-1,j+1} - t_{i+2,j+1}| + |t_{i+1,j-1} - t_{i+1,j+2}| + |t_{i-1,j+1} - t_{i+1,j+1}| + |t_{i+1,j+1} - t_{i+1,j+1}| + |t_{i-1,j-1} - t_{i+1,j-2}| + |t_{i+1,j+1} - t_{i+1,j+1}| \right)$$

$$V_{max} = \sum_{i=1}^{M} \sum_{j=1}^{N} V_c(t_{i,j})$$

In our adaptive technique, a heuristic matrix $\eta_{i,j}$ is evaluated based on the local statistics of the image which depends on the clique. Clique is defined as the groups of ants connected or taken together. In our problem 8-connectivity is taken as clique mode. The local information of the pixel at the position $(i, j)$ is given by Eq. (1)

$$\eta_{i,j} = \frac{v_c(t_{i,j})}{v_{max}}$$

Where

$$V_c(t_{i,j}) = f \left( |t_{i-1,j-1} - t_{i+1,j+1}| + |t_{i-1,j+1} - t_{i+2,j+1}| + |t_{i+1,j-1} - t_{i+1,j+2}| + |t_{i-1,j+1} - t_{i+1,j+1}| + |t_{i+1,j+1} - t_{i+1,j+1}| + |t_{i-1,j-1} - t_{i+1,j-2}| + |t_{i+1,j+1} - t_{i+1,j+1}| \right)$$

$$V_{max} = \sum_{i=1}^{M} \sum_{j=1}^{N} V_c(t_{i,j})$$

Where
Fig. 4. The configuration of the pixel at the position \((i,j)\) to calculate the value of \(V_c(I_{i,j})\) which is in Eq. (2).

\(V_{\text{max}}\) is the maximum intensity variation in the image and serves as a normalization factor. \(I_{i,j}\) is the intensity value of the pixel at the position \((i,j)\).

A function \(V_c(I_{i,j})\) is a local group of pixels called clique. The clique matrix is given in Fig. 4.

The function \(f(x)\) developed in Eq. (2), can be defined with the following mathematical forms:

\[
f(x) = \lambda x \quad (4)
\]

\[
f(x) = |x^2| \quad (5)
\]

\[
f(x) = \begin{cases} 
\sin \left(\frac{\pi x}{2}\right) & 0 \leq x \leq \lambda \\
0 & \text{else}
\end{cases} \quad (6)
\]

\[
f(x) = \frac{\pi x \sin \left(\frac{\pi x}{2}\right)}{\lambda} \quad 0 \leq x \leq \lambda \quad (7)
\]

The parameter \(\lambda\) in \(f(x)\) adjusts the functions’ respective shapes.

**Construction Step**

At each construction step, one ant is randomly selected and this ant will consequently move on the image for \(L\) movement steps. Ant move from the pixel \((i,m)\) position to \((i,j)\) position with the probability given as

\[
P_{(i,m),(i,j)}^{(n)} = \frac{\tau_{i,j}^{(n-1)}}{\sum_{(i',j') \in \Omega_{(i,m)}} \tau_{i',j'}^{(n-1)}} \quad (8)
\]

\(\tau_{i,j}^{(n-1)}\) represents the pheromone value at a pixel \((i,j)\) \(\Omega_{(i,m)}\) is the neighborhood
nodes of the node \((l,m)\), \((\eta_{l,m})\) represents the value of heuristic matrix at the node \((l,m)\). The value of the constants and influences the pheromone matrix and heuristic matrix respectively.

**Update Process**

The first update is done on the pheromone matrix after each ant is moved within each \(n^{th}\) construction step which is as follows:

\[
\tau_{i,j}^{(n-1)} = \begin{cases} 
(1 - \rho) \cdot \tau_{i,j}^{(n-1)} + \rho \cdot \Delta_{i,j}^{(k)} & \text{if } (i,j) \text{is the best tour} \\
\tau_{i,j}^{(n-1)} & \text{otherwise}
\end{cases}
\]  

(9)

The second update process is done after all ants are moved within each \(n^{th}\) construction step which is as follows:

\[
\tau^{(n)} = (1 - \psi)\tau^{(n-1)} + \psi\tau^{(0)}
\]  

(10)

Where \(\rho\) is considered as the evaporation rate and \(\psi\) is considered as the pheromone decay coefficient.

**Decision Process**

In this process, the edge is detected by the pheromone matrix based on the threshold value. The above threshold value is computed based on the [29]. The iterative procedure to calculate the edge can be given as follows:

1) *Initialize matrix:* Initially \(\tau^{(0)}\) is calculated as mean value of the pheromone matrix.

\[
\tau^{(0)} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \tau_{i,j}^{(0)}}{MN}
\]  

(11)

Now set iteration index as \(l = 0\).

2) *Calculate mean:* Separate the pheromone matrix \(\tau^{(n)}\) into two class using \(\tau^{(l)}\), where the first class entries of \(\tau\) have smaller values than \(\tau^{(l)}\), while the second class consists the rest entries of \(\tau\). Now calculate the mean of each of the above two values from the formulae given in (12) and (13)

\[
m_{ij}^{(l)} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \tau_{i,j}^{(l)} \cdot g_{\tau(0)}^{l}(\tau_{i,j}^{(l)})}{\sum_{i=1}^{M} \sum_{j=1}^{N} \tau_{i,j}^{(l)} \cdot g_{\tau(0)}^{l}(\tau_{i,j}^{(l)})}
\]  

(12)

\[
m_{ij}^{(l)} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} \tau_{i,j}^{(l)} \cdot h_{\tau(0)}^{l}(\tau_{i,j}^{(l)})}{\sum_{i=1}^{M} \sum_{j=1}^{N} \tau_{i,j}^{(l)} \cdot h_{\tau(0)}^{l}(\tau_{i,j}^{(l)})}
\]  

(13)

\[
g_{\tau(0)}^{l}(x) = \begin{cases} 
x, & \text{if } x \leq \tau^{(l)} \\
0 & \text{otherwise}
\end{cases}
\]  

(14)

\[
g_{\tau(0)}^{u}(x) = \begin{cases} 
x, & \text{if } x \geq \tau^{(l)} \\
0 & \text{otherwise}
\end{cases}
\]  

(15)

\[
h_{\tau(0)}^{l}(x) = \begin{cases} 
1, & \text{if } x \leq \tau^{(l)} \\
0 & \text{otherwise}
\end{cases}
\]  

(16)

\[
h_{\tau(0)}^{u}(x) = \begin{cases} 
1, & \text{if } x \geq \tau^{(l)} \\
0 & \text{otherwise}
\end{cases}
\]  

(17)

3) *Update threshold:* Set the iteration index, \(l = l + 1\) and update the threshold as

\[
\tau^{(l)} = \frac{m_{ij}^{(l)} + m_{ij}^{(l)}}{2}
\]  

(18)
4) Determine edge: If \( |T(i) - T(i-1)| > \epsilon \) then goto step 2; otherwise the iteration process is terminated. The binary decision is made on each pixel position \((i, j)\) to determine whether it is an edge or not based on the criterion

\[
E_{i,j} = \begin{cases} 
1, & T_{i,j}^{(0)} \geq T^{(0)} \\
0, & \text{otherwise}
\end{cases}
\]  

(19)

The images of palmprint after edge detection using ACS are given in Fig. 5.

![Fig. 5. (a) Actual palmprint image (b) ACO based edge detected image of the actual image](image_url)

4. Feature Extraction using Gabor Filter

There are various categories to extract the features from the pre-processed images. In our proposed approach palmprint image which is edge detected from the previous step. It is taken as the input and applied to the Zhang et al [34] based gabor representation. Gabor filter was proposed by an electrical engineer named Dennis Gabor in 1946 as a one-dimensional wavelet. Later the function was extended to two dimensional in [31] by Daugman. The various interesting properties of 2D gabor function which are given in [32] are as follows: Gabor functions are jointly generalized in a spatial and preferred orientation which makes the gabor function to act as a local band-pass filter. Neuroscience studies have shown that receptive fields of simple cells of the primary visual cortex of primates can be modeled by gabor functions. The various applications of gabor functions are corner detection, document analysis, fractal dimension management, blob detection, feature extraction and image segmentation. Gabor function is defined as gaussian function modulated by the sinusoidal plane wave which is given in Eq. (20). The gaussian functions given by Carl Friedrich Gauss is in Eq. (21) are widely used in mathematics and statistics. They describe the normal distributions in signal processing and serve in gaussian filters and gabor filters in image processing domain. Gabor filters are self-similar in which all the filters are generated from mother wavelet by dilation and rotation.

\[
f(x) = ae^{-\frac{(x-b)^2}{2\sigma^2}}
\]  

(20)

\[
g(x) = f(x) \cdot s(x)
\]  

(21)

\(f(x)\) is known as the carrier which is the Gaussian function for the given
constants $a$, $b$, and $c$. Where $e$ is the Euler's number and $s(x)$ is known as the envelope. The gabor function is a special case of Short Time Fourier Transform (STFT) analysis in which kernel is applied to examine the signal in both time and frequency domains. Gabor filter is used to extract the texture features of wrinkles and principle lines of the edge detected palmprint image of different scales and orientations. Gabor filter actually comes in pairs as symmetric (even) and anti-symmetric (odd) function. An odd (sine) Gabor function is the partial differential order of even order. An even (cosine) function is the partial differential order of odd order. The Eq. (22) and Eq. (23) represent the gabor even and gabor odd function respectively.

$$g_e(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right)} \cos(2\pi\omega_{x_0}x + 2\pi\omega_{y_0}y) \quad (22)$$

$$g_o(x, y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2} \left( \frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2} \right)} \sin(2\pi\omega_{x_0}x + 2\pi\omega_{y_0}y) \quad (23)$$

$$g(x, y) = g_e(x, y) + ig_o(x, y) \quad (24)$$

Where $(\omega_{x_0}, \omega_{y_0})$ defines the center frequency and $(\sigma_x, \sigma_y)$ the spread of the gaussian window. The gabor filter is finally given in Eq. (24). The image is now convolved with the gabor filter using real and imaginary values to form the gabor space. The convolution is applied for various rotations which are in the range of $[0, \pi]$.

$$l_t = \text{conv2}(l, \text{imag}(g(x, y))) \quad (25)$$

$$R_t = \text{conv2}(l, \text{real}(g(x, y))) \quad (26)$$

$$G_{fr} = \sqrt{l_t^2 + R_t^2} \quad (27)$$

After edge detection, palmprint image ($l$) of size 20 x 20 is taken as input and applied to the Eq. (25) and Eq. (26) in the range of $[0, \pi]$ orientation which results in the imaginary and real images of gabor filter respectively. The Gabor Filtered ($G_{fr}$) image using both real and the image is given in Eq. (27). The real images and gabor filtered images are given in Fig. 6 and Fig. 7. The real images represent the results of $(\pi/6, 2\pi/6, 4\pi/6, \text{and } 5\pi/6)$ orientations. The results of gabor filter at 0, 3 $\pi/6$, and at $\pi$ is almost nil.

Fig. 6. Real images of palmprint after applying gabor filter
5. Experimental Results

In this section, multiclass Support Vector Machine (SVM) is explained along with the results of the classification of palmprint data. Support Vector Machine is one of the types of supervised learning methods in pattern recognition. This classification was invented by Vladimir N. Vapnik in 1992. The purpose of SVM is to predict the test data from the train data of different classes. The test data is labeled as unknown and train data is labeled as known. Initially, SVM was designed for the binary classification. Later SVM was developed for multiple classes. The various approaches for developing multiple classes are given as One vs Rest, One vs One, Directed Acyclic Graph (DAG), and Error Corrected Output Coding (ECOC). Our work is based on the first two approaches.

One Against Rest Approach

In this approach, we have to divide the dataset into N classes. Hence we create the N binary classifiers where each binary classifier is trained to divide the dataset from the remaining N-1 classes. In the testing phase, data vectors are classified by finding margin from separating linear hyperplane. We get the final output from the plane that corresponds to the SVM with the largest margin. The largest margin is based on the decision function value. The decision function can be given as follows:

\[ c(x) = \arg \max_{0 \leq x \leq 1} f_i(x) \]  \hspace{1cm} (28)

\( f_i(x) \) is the output of the SVM classifier of binary category trained for class \( i \) against all other classes.

This approach is also called as the winner takes all classification or One-Against-All (OAA) approach. This technique has an advantage in which the numbers of binary classifiers are needed to construct an equal number of classes. The memory required to implement the training will be at the square of the training samples which is very high. The second scenario is that if all the classes have an
equal number of training data, the ratio of training samples of one class to rest of the classes will be $1:(N-1)$ in a total of $N$ classes. This ratio suggests the imbalanced training sample size. To overcome the above drawbacks the one against one approach has been implemented.

**One Against One Approach**

In this method, for $N$ classes we require $N(N-1)/2$ binary SVM classifiers. Each classifier is trained to separate each pair of classes. We combine the binary classifiers using pairwise coupling technique suggested by Hastie and Tibshirani in [32]. This pairwise coupling strategy combines the probabilistic outputs of all the one-versus-one binary classifiers to obtain the estimates of posterior probabilities as given in Eq. (29) as follows:

$$P_i = \text{Prob}(\omega|\mathbf{x})$$  \hspace{1cm} (29)

After these are estimated, the pairwise coupling strategy assigns the example under consideration to the class with the largest $P_i$, where $i = 1...N$. The decision function in OAO approach can be given as follows:

$$c(\mathbf{x}) = \arg \max_{0 \leq x \leq 1} P_i(\mathbf{x})$$  \hspace{1cm} (30)

The number of classifiers created by this method is generally much larger than the previous method. But for each classifier, the number of training data vectors required is much smaller. Whereas the relative amount of training data size for one class against another is also small. Therefore, this method is considered more symmetric than the OAA method. The main advantage of this method is small memory required to generate the kernel matrix. However, the major drawback of this technique is an increase in the number of classifiers as the number of classes increases.

**Performance Evaluation**

The performance of the proposed algorithm is evaluated using the palmprint database taken from the Hong Kong Polytechnic University [34]. The database is divided into two sets which consist of training data and testing data. From the PolyU palmprint database, 100 samples are taken at random. Each sample consists of 20 images taken in two different instances. During training 7 images are considered whereas for testing 4 images are taken. For classification of features, multiclass SVM algorithm is implemented with two approaches: (i) One-Against-All (ii) One-Against-One. The experimental results are performed with Intel Core 2 Duo processor having Matlab version 8.0 with image processing toolbox and 2 GB RAM.

The popular tool to evaluate the performance model in predicting the particular class is confusion matrix which is depicted in Table 2. The confusion matrix is used to measure the performance of classifier using the practical reports of True positive, False positive, True Negative and False Negative. Classification rate of any classifier is the measure of the ratio of correctly classified testing data against the total testing data which is clearly stated in Eq. (31). The other
important performance measures of the application are False Acceptance Rate (FAR), Genuine Acceptance Rate (GAR), and False Rejection Rate (FRR). The False Acceptance Rate is the percentage of invalid inputs which are incorrectly accepted. Genuine Acceptance Rate is also known as Detection rate. It is defined as the percentage of acceptance of authorized users in total identification attempts. The False Rejection Rate is defined as the percentage of valid inputs which are incorrectly rejected. The definitions of FAR, FRR and GAR are given in Eq. (32), Eq. (33) and Eq. (34) respectively.

\[
\text{Classification rate} = \frac{\text{Number of correctly classified testing data}}{\text{Total number of testing data}}
\]  

(31)

\[
\text{FAR} = \frac{\text{Number of accepted poseur claims}}{\text{Total number of poseur access}} \times 100
\]  

(32)

\[
\Phi PP = \frac{\text{Number of rejected genuine claims}}{\text{Total number of genuine access}} \times 100
\]  

(33)

\[
\text{GAR} = (1 - \text{FRR}) \times 100
\]  

(34)

The formula for evaluating the confusion matrix is given in Table 3. The various metrics of confusion matrix obtained from the classification results for two approaches of multi-class SVM are tabulated in Table 4.

From the below results, we came to know that FAR and GAR of OAO is 0.83 and 90.24 respectively whereas for OAA is 1.11 and 87.8 respectively. The classification rate of OAO is 92.5 which are higher when compared with OAA of 90. From the results, the performance and accuracy of OAO are better than OAA. The performances of two classifiers of multiclass Support Vector Machine and classification rate of OAO and OAA are represented in the form of a graph in Fig. 8 and Fig. 9.

The comparison of various existing approaches with the proposed approach is given in Table 5.

<table>
<thead>
<tr>
<th>TABLE II. CONFUSION MATRIX</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Actual Class</strong></td>
</tr>
<tr>
<td>Positive</td>
</tr>
<tr>
<td>Negative</td>
</tr>
<tr>
<td>P</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE III. PERFORMANCE TECHNIQUES OF SVM CLASSIFIER</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Formula</strong></td>
</tr>
<tr>
<td>ACC</td>
</tr>
<tr>
<td>TPR</td>
</tr>
<tr>
<td>TNR</td>
</tr>
<tr>
<td>AUC</td>
</tr>
</tbody>
</table>
TABLE IV. RESULTS OF SVM CLASSIFIER

<table>
<thead>
<tr>
<th>Performance Measures</th>
<th>Multi class Approaches</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>One against One</td>
</tr>
<tr>
<td>TPR</td>
<td>90.24</td>
</tr>
<tr>
<td>TNR</td>
<td>99.1643</td>
</tr>
<tr>
<td>FAR</td>
<td>0.83</td>
</tr>
<tr>
<td>FRR</td>
<td>9.75</td>
</tr>
<tr>
<td>GAR</td>
<td>90.24</td>
</tr>
<tr>
<td>ACC</td>
<td>98.25</td>
</tr>
<tr>
<td>Classification</td>
<td>92.5</td>
</tr>
</tbody>
</table>

Fig. 8. Performance of multi-class SVM

Fig. 9. Accuracy and classification rate of OAO and OAA
6. Conclusion

The palmprint recognition is considered as personal authentication technique based on the characteristics it possesses. In this research work, a new hybrid approach named ACO based edge detection algorithm is introduced. In the feature extraction phase, 2D gabor filter was applied to the ACS edge detected images to extract the features of the palmprint images. In the classification phase, the approaches of multiclass SVM namely OAO and OAA are applied on the training and testing data of the palmprint database. The experimental results performed on PolyU palmprint database gives various conclusions. The FAR of OAA is 1.11 which is higher when compared to FAR of OAO which is 0.83 whereas GAR of OAA is 87.80 which is lower when compared to 90.24 of OAO. The classification rate of OAO is 92.5 which is better than 90 of OAA. From the results, we come to know that classification of multiclass SVM using OAO approach gives better results. The drawbacks of using various conventional edge detection approaches can be overcome by using ACS and it gives the advanced performance over the existing algorithms. The future work of the proposed methodology is to increase the dataset to improve the results and also to implement the algorithm using various neural network classifiers. Still, the
ongoing research work is to reduce the computational complexity using ACO parallel algorithm.

**Acknowledgment**

This work was supported by Tagore Engineering College, Chennai, India, for providing the materialistic resources and also to my co-authors for helping me in developing the report.

**References**


[34] www.comp.polyu.edu.hk/~biometrics/2D_3D_Palmprint.html.