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INITIAL ACCEPTANCE LETTER

Dear Jitendra Chaudhari, Pradeep M Patil, Y P Kosta
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After having carefully evaluated your article titled “Computation less Radon based Palmprint Characterization” and taken the referees' advice into consideration, the editors came to the conclusion that your paper is suitable for publication in our Journal. In order to save time, the referees communicated their opinion to us verbally. As part of our evaluation process, we normally ask the opinion of two referees who are experts in the relevant field of research. The paper is also read by the editor. If both of the referees and an editor concur in their view, their decision is final. We consult a third referee if there is a difference of opinion. In order to expedite the proceeding, which is one of the objectives of the journal, we do not require a full report on the paper from the referees.

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Multimodal biometric-information fusion using the Radon transform

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Multimodal biometric-information fusion using the Radon transform

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Abstract. This paper proposes multimodal biometric-based personal identification. Palmprint and fingerprint modalities are utilized in the proposed model due to the availability of more distinctive features and the ease of capture. Principle lines are the main discriminative features in the palmprint, whereas orientations of the ridge and valley structures are the main features by which to identify the fingerprint. To extract these features, the use of the Radon transform is proposed in this work. However, the Radon transform is sensitive to the orientation. In order to make the model rotation invariant and insensitive to noise, a normalization process is generally used. Here, a logarithm-based normalization process has been utilized in the proposed model. A Euclidean-based matching process that is invariant to the rotation has been used. The proposed model is applicable to low resolution images and is invariant to rotation, insensitive to noise, and has less computational complexity as compared to other models. © 2015 SPIE and IS&T [DOI: 10.1117/1.JEI.24.2.023017]

Keywords: fingerprint; fusion; multimodal biometric; palmprint; person identification; Radon transform.

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1 Introduction

Biometric identification has replaced and strengthened the earlier password and token-based system as it requires physical interaction with the system. Normally, a biometric system uses one modality for identification purposes usually called a unimodal biometric system. The unimodal biometric system using modalities such as fingerprints, faces, and voice is fairly vulnerable to many problems such as nonuniversality, spoof attacks, and so on. It results in a high false rejection rate (FRR) and false acceptance rate (FAR). Therefore, the solution to overcome these limitations is the multimodal biometric where two or more modalities are jointly used to validate identity. Table 1 shows a comparison of different biometric technologies based on the perception of the authors. However, due to a higher error rate, the present multimodal biometric system proposed in much literature is not suitable for online recognition systems.

Biometric systems have replaced and strengthened the earlier password and token-based systems as they require physical interaction with the system. Normally, a biometric system uses one modality for identification purposes.

A multimodal biometric system involves the utilization of more than one modality for identification purposes such as the iris and finger, finger and palm, face and palm, finger and face and so on. A multimodal biometric system has been previously proposed in numerous works. From Ref. 1, it is found that except for fingerprint and hand geometry (palmprint), the remaining modalities all have a weakness in their characteristics. Therefore, in this paper, we have proposed the use of fingerprints and palmprints to develop a multimodal biometric system. The basic requirement for multimodal biometric systems is the fusion of these modalities.

2 Fusion Levels

Fusion of these modalities can be achieved at four different levels; namely, sensor level, feature level, match level, and decision level. A brief discussion about these levels is as follows:

- Sensor-level fusion: for multisample systems, the samples can be combined to form a single sample. For example, live scan fingerprint devices create a single large “rolled” image from a series of individual fingerprints.
- Feature-level fusion: feature extractor software converts samples (images) into simplified computer representations known as templates or feature sets. In template-level fusion, multiple templates are combined to form a single template.
- Match-level fusion: This refers to methods in which multiple samples, instances, or modalities are compared and the resulting similarity scores (or probabilities) are combined to form a single fused score. Match-level fusion can also be used to combine the results of multiple algorithms when a single sample is searched.
- Decision-level fusion: This is used in many of the same cases as score-level fusion, but the scores are turned into a match/nonmatch decision before fusion.

If we compare the feature-level fusion and match-level fusion with the decision-level fusion, the decision-level
fusion has the least fusion complexity, along with the maximum interoperability across different biometric features, templates, formats, template protection, recognition algorithms, and comparison score rules. The only drawback of the decision level fusion is that the fusion at the decision level is too rigid since only a limited amount of information is available at this level.\textsuperscript{2}

3 Related Work

The previous work on multimodal biometric fusion focused on different techniques for feature extraction. Some of the work presented the following techniques.

3.1 Gabor and/or Wavelet-Based Feature Extraction Method

Aly et al.\textsuperscript{9} used a log-Gabor wavelet filter to extract the features of face and palm. These features are fused at the match level along with the features extracted from finger-knuckle points. Chin et al.\textsuperscript{10} did fusion of palmprints and fingerprints at the feature level with a Gabor wavelet transform technique used for feature extraction. The Gabor filter generated features depend on the selection of three parameters, namely, frequency, scale, and variance. They investigated the effect of the length of features at the feature-level fusion model. For better accuracy, more features are required at the fusion level. Deepak and Ashok\textsuperscript{11} proposed a feature-level fusion of face and iris using the log-Gabor filter and a local binary pattern. Similarly, He et al.\textsuperscript{12} proposed a match level-based fusion technique using a log-Gabor filter. To avoid redundancy, particle swarm optimization method is utilized to achieve a proper Gabor filter with respect to the modality. Match-level fusion is used by fusing the score of the normalized response of a one-dimensional log-Gabor filter.\textsuperscript{13} They demonstrated the results with 0.012\% FAR and 1.569\% FRR. It is observed that Gabor wavelet transform has three main disadvantages, shift sensitivity, poor directionality, and the absence of phase information.

3.2 Principal Component Analysis-Based Feature Extraction Method

The principal component analysis (PCA) method is utilized to reduce the data size. Nadheen and Poornima\textsuperscript{14} proposed a multimodal biometric system using iris and ear. The features of each modality are extracted using the PCA method and sum-based match-level fusion is utilized. This fusion work shows a 95\% accuracy. Feature-level fusion is utilized where features are extracted using Gabor filters and the dimensions of feature vectors are reduced using the PCA and LDA methods.\textsuperscript{15}

3.3 Support Vector Machine-Based Feature Extraction Method

Support vector machine (SVM) is a powerful statistical classification tool. It can be used as a fusion tool for multimodality. Fahmy et al.\textsuperscript{16} fused the iris and fingerprint at match level using the SVM. They proposed that normalization is an important step for better accuracy. The fusion of iris and face at the match level has been carried out in Ref 17. In this method, the Euclidean distance-based Laplacian face and the phase of the iris are utilized. Dinerstein et al.\textsuperscript{18} proposed the fusion of three modalities at the match level as Iris, DNA, and Face. They used multiple SVM and appropriate features from those SVMs were used in the fusion process. Geethu et al\textsuperscript{19} proposed match-level fusion of the iris and fingerprint using multiple SVM.

SVM has good generalization properties and is found to be accurate for smaller numbers of training samples. The major limitations of SVM are the training time and difficulty in its parameter selection.\textsuperscript{20}

\begin{table}[h]
\centering
\begin{tabular}{|l|c|c|c|c|c|c|c|}
\hline
Biometric identifier & Universality & Distinctiveness & Permanence & Collectability & Performance & Acceptability & Circumvention \\
\hline
Face & H & L & M & M & L & H & H \\
Facial thermogram & H & H & L & H & M & H & L \\
Fingerprint & M & H & H & M & H & M & M \\
Gait & M & L & L & H & L & H & M \\
Hand geometry & M & M & M & H & M & M & M \\
Iris & H & H & H & M & H & L & L \\
Palmprint & M & H & H & M & H & M & M \\
Voice & M & L & L & M & L & H & H \\
Retina & H & H & M & L & H & L & L \\
DNA & H & H & H & L & H & L & L \\
Keystroke & L & L & L & M & L & M & M \\
\hline
\end{tabular}
\caption{Comparison of various biometric technologies based on the perception of the authors of Ref. 1. H indicates high, M indicates medium, and L indicates low.}
\end{table}
3.4 Zernike Moment-Based Feature Extraction Method

In the Zernike moment, the two-dimensional metric is projected using an orthogonal basis function. The magnitude of the Zernike moment is invariant to the rotation, translation, and scaling. Thus, the Zernike moment has a powerful potential to extract the features of biometrics. With this, many works have proposed using the biometric features extraction method using Zernike moments. Again, the use of high-order moments preserves more features. Based on the method in Ref. 21, finger and palm features are fused using higher-order Zernike moments. Different parts of the hands are utilized at the feature level, match level, and decision level. The limitation of this model is that as the model is based on the segmentation of finger and palm, the touching of fingers must be avoided during image acquisition.

The Zernike moment is invariant to rotation which is the basic requirement for multimodal identification and it has a higher recognition rate. However, a high order of Zernike moments is needed to improve the recognition rate and it is found that the computation time also increases with order size.22

3.5 Radon-Based Feature Extraction

Radon transform holds a distinguishable place in the field of biometrics. It has been utilized in face recognition,23,24 iris recognition,25 and fingerprint recognition. The Radon transform is calculated at 0 deg and 90 deg to extract the core of the fingerprints.26 To make the recognition algorithm independent of the image acquisition device, the Radon transform is found to be most suitable technique. Based on that, this paper proposed the use of the Radon transform for feature extraction of modalities.

4 Proposed Work

4.1 Modality Selection

Biometrics commonly implemented or studied include fingerprint, face, iris, voice, signature, and hand geometry. Facial recognition does not require the direct contact of human and machine. It only requires that a camera capture an image. A higher computational cost is required due to the need for processing a large amount of data in the case of three-dimensional facial recognition. Biometric systems using iris scan are highly accurate, but these systems require proper alignment and positioning.

The speaker/voice recognition, contactless system, becomes insufficiently distinctive for identification over large databases, also faces difficulties in controlling sensor and channel variances that significantly impact capabilities in signature-based and verification-based systems. In signature-based system, inconsistency in signature causes difficulty of enrolling and verifying the individual’s signature.

From Table 1, it can be analyzed that except for fingerprint and hand geometry, all biometrics face weaknesses in at least one of the characteristics. Therefore, fingerprint and hand geometry can be considered as a true combination as compared to other possible biometric pairs.

Every individual has unique fingerprint features. The ridges and the valleys are the features which are extracted for authentication. Thorough research on fingerprint recognition has shown that fingerprints are not distinguished by their ridges and valleys, but by other characteristics of fingers called minutia.27–29

The palm possesses more features as compared to other modalities. The palmprint matching approach can be based on low resolution features (principal lines, wrinkles, and texture) and high resolution features (singular points, minutiae, and ridges).30

4.2 Proposed Radon-Based Multimodal System

Radon transform gives the spatial distribution of energy, the Radon transform parameterized the lines \( ax + by = c \) to a set of oriented lines with radial parameters as shown in Fig. 1:

Considering the general line \( ax + by = c \), where \( a, b \), and \( c \) are the constants, we can define the points on a unit circle using the equation

\[
\begin{align*}
\frac{a}{\sqrt{a^2 + b^2}} x + \frac{b}{\sqrt{a^2 + b^2}} y &= \frac{c}{\sqrt{a^2 + b^2}},
\end{align*}
\]

where points are described using the two coefficients \( (a/\sqrt{a^2 + b^2}, b/\sqrt{a^2 + b^2}) \). Let \( \theta \) be the angle corresponding to the points defined using the above equation. Then

\[
\begin{align*}
\theta &= \cos^{-1} \left( \frac{a}{\sqrt{a^2 + b^2}} \right), \\
\cos(\theta) &= \frac{a}{\sqrt{a^2 + b^2}} \\
\sin(\theta) &= \frac{b}{\sqrt{a^2 + b^2}}.
\end{align*}
\]

The angle can take values of \([0, \pi]\). Let \( t \) represent the distance of lines from the origin along the angle \( \theta \). Then lines can be represented using this distance as a solution of equation \( t = \langle (x, y), \cos \theta, \sin \theta \rangle = \langle (x, y) \rangle \).

Let vector \( \omega = \langle \cos \theta, \sin \theta \rangle \) be perpendicular to line \( ax + by = c \). The corresponding orthogonal vector

![Image](335x77 to 556x298)

**Fig. 1** Parameterization of line to \( l_{\theta}. \)
\( \hat{\omega} = \langle (\cos \theta, \sin \theta) \rangle \) is then parallel to the line. Using these, a vector equation in terms of \( t \) and \( \theta \) can be created for the lines

\[
l_{t,\theta} = tw + s\hat{\omega} = \langle t \cos \theta, \sin \theta \rangle + s\langle -\sin \theta, \cos \theta \rangle.
\]

Considering some function \( f \) parameterized over the lines \( l_{t,\theta} \), the Radon transform is defined as

\[
rf(t, \theta) = \int_{l_{t,\theta}} f ds = \int_{-\infty}^{\infty} f(tw + s\hat{\omega}) ds
\]

\[
= \int_{-\infty}^{\infty} f(t \cos \theta - s \sin \theta, t \sin \theta + s \sin \theta) ds.
\]

As the Radon transform is the line integral of the image, the Radon transform of noise is constant for all the points and directions and is equal to the mean value of the noise, which is assumed to be zero. The palmprint contains features in terms of principle lines and these principle lines can be easily accessed even in low resolution images. Therefore, in the proposed model, the Radon transform is utilized to characterize the principle lines of the palmprint. For fingerprints, the orientations of ridges and valleys are the main features for identification and the Radon transform has the capability to precisely extract these features. It is found that the Radon profile from various acquisitions of the same finger is similar while it generates a different Radon profile for the distinct figures.\(^3\)

Figure 2 represents the Radon profile for three fingerprints, where \( F_{1_a} \) and \( F_{1_b} \) are the fingerprints of the same individual and \( F_2 \) is the fingerprint for another individual. The graph shows that correlation is higher amongst \( F_{1_a} \) and \( F_{1_b} \) in comparison with that of \( F_{1_a} \) and \( F_2 \).

Similarly Fig. 3 represents the Radon profile for three palmprints, and the graph shows that correlation. Using this concept, the Radon is utilized in the proposed model for the person identification.

### 4.3 Radon-Based Feature Extraction

Since web cam resolution is less, the variation in captured image is very slow and sharpness is also low. Therefore it is difficult to extract the ridges. Its principle lines are invariant to the illumination changes. As Radon can be utilized to successfully extract the principle lines from a palmprint, we propose the Radon-based model to extract the features of the palm using principle lines.

The Radon transform is calculated over a number of orientations. In the fingerprint, the ridges and valleys are characterized by the orientations. Thus, Radon transform can easily extract the ridges and valleys features from a fingerprint. As the Radon transform integrates all features at each orientation, the Radon profile of noise is always constant and it is equal to the mean of noise which is assumed to be zero. Thus, the Radon transform provides noise insensitive features’ extraction from the fingerprint.

To validate the noise of Radon features, the plot showing a comparison of histogram of Radon for fingerprint and palmprint images are shown in Fig. 4. Here, additive white Gaussian noise with a zero mean and 0.15 variance is added to the original fingerprint image to obtain the noisy fingerprint. It can be seen that the correlation among the histogram of Radon of the original fingerprint/palmprint (blue color), noisy fingerprint/palmprint (red color), and fingerprint/palmprint of same individual (black color) is higher than the correlation between that of two different individuals (i.e., original fingerprint/palmprint and fingerprint/palmprint of another individual (green color)).

The palmprints and fingerprints are utilized from the regular databases, i.e., PolyU database\(^3\) and FVC-2004\(^3\)\(^3\) database, respectively, where all the databases are in gray
scale format. Palmprints and fingerprints have a spatial resolution of $128 \times 128$ (75 ppi) and $640 \times 480$ (96 ppi), respectively.

The proposed model uses the Radon algorithm and, as discussed earlier, Radon detects the lines in an image. To process the image and to extract the Radon-based features of an individual, each biometric is preprocessed using the edge-detection model. To extract the edges, a number of filters are available such as Canny, Prewitt, Laplacian filter, and so on. However, the biometric recognition has a very large database and again it is a multimodal recognition technique. Therefore, the identification of a single user requires the comparison of two biometric prints within a huge database. Hence, to reduce the preprocessing time in the proposed model, the Laplacian filter has been utilized in comparison to other edge-detection filters.

In Refs. 5 and 34, singular value decomposition is applied to the Radon transform of fingers, knuckle images and palmprints and features are extracted using the gradient-based model. These futures are fused at the decision level for personal identification.

Due to need for rotation invariance and translation invariance, a histogram of Radon is utilized.

Histogram equation:

$$HR^\theta(k) = \frac{R^\theta_k}{|R(t, \theta)|},$$

where $|R(t, \theta)|$ represents the total length of the Radon feature vector at orientation $\theta$.

This histogram represents the features at each orientation level. The major requirement of any biometric identification process is that they must be invariant to rotation, translation, and scaling. A shifting operation implies variation along the radial parameter. In the proposed model, the histogram is calculated at every angle and, therefore, remains unchanged. The Radon transform is sensitive to the rotation of an image.
Therefore, a change of orientation causes a shift in the angular parameter of the Radon transform, i.e.,

\[ HR^0(k) = HR^\theta + \theta, \theta \in [0, \pi). \]

This variation in the rotation causes the shifting of histogram values at another orientation and this causes a problem in the matching process. As a solution, the matching process which is invariant to rotation is employed using Euclidean distance. To obtain the scaling invariance, in most of the literature, a normalization process is utilized. However, this normalization process generates an error and is also highly sensitive to the noise. Thus, to avoid the normalization process and to make the features invariant to scaling, a logarithm normalization process is utilized in the proposed model. Thus, using a normalization process, the histogram of Radon is given as

\[ HR^0(k) = H\{ln|R^\theta(k)|\}. \]

The last step in multimodal biometric features database generation is the fusion of the obtained features. In the proposed model, fusion is applied at the decision level. Fusion at the decision level has the advantage of being the simplest. At the decision level, various approaches are presented in the literature, i.e., by providing weightage to the features of each modality, or using various arithmetic and/or logical operations such as min, max, addition, AND, or XOR operations between the features of two modalities. In the proposed model, the features of both modalities are concatenated at each orientation. The features extracted from palmprints and fingerprints are the features extracted at various orientations of the image. To increase matching accuracy, it is desirable to use maximum orientations. In the proposed model, 180 orientations are utilized to calculate the Radon transform.

Identification is achieved by matching the stored template with the query image. In the proposed model, the stored template contains the fused histogram of palmprints and fingerprints at various orientations. The correlation between the template of the query image and the stored template is calculated to identify the person. The correlation achieves maximum values when identical modalities are compared with each other. As previously suggested, the rotation of the modality causes a shift in the histogram. To make the matching process invariant to the rotation, the histogram of the query image is rotated in steps and the correlation for each rotation is calculated. The maximum value of the calculated correlation is considered as the matching point.

\[ C = \max\{\text{corr}(HR^0_{\text{query},n} - \text{rotate}_n(HR^0_i))\}, \]
\[ n = 1, 2, \ldots, \text{length}(\theta). \]

5 Experimental Results and Discussion

In the proposed model, 60 images with four subsets per individual are utilized for both fingerprints and palmprints. These databases are obtained from FVC-2000 and PolyU32 to check the performance of the proposed model. The features’ extraction and matching are carried out using the following steps:

1. Preprocess the modalities to enhance the features.
2. Calculate the Radon transform of both the modalities.
3. Obtain the histogram of Radon and calculate the logarithm to obtain the scale invariant features.
4. Prepare the database by fusing the features of fingerprint and palmprint.

In the proposed model, 180 angles are utilized in the Radon transform. To obtain the feature vector, a 10-bin histogram is calculated for Radon coefficients. To match the query images, the following steps are utilized:

1. Carry out step 1 to step 3 for feature extraction.
2. Fuse the features of the query images and calculate the correlation with the database features. To obtain rotation invariant matching, features of the query images are rotated and correlation is calculated.
3. The maximum correlation provides the match of the query image.

Thus, to match one query image, 240 correlation operations within the database are needed. The average matching time for the given database is 0.081 s.

To identify the individual, the template of one individual is compared with the templates of other individuals. This template is also compared with its own three subsets. The inverse correlations among seven templates from the considered datasets (60 templates) are shown in Fig. 5, i.e., each column represents the inverse correlation of a template with the remaining six templates. It can be seen that when the identity is compared with itself, the inverse correlation is zero. However, when it is compared with other identities, the inverse correlation exists.

As previously stated, in the proposed model, four subsets per individual are utilized. When the identity is compared with its own subsets, the inverse correlation should be less. To illustrate it, the inverse correlations of template 2 with its remaining three subsets and with other six identities from the database are represented in Fig. 6. From figure, it can be observed that the inverse correlations between template...
2 and its subsets are less in comparison to the inverse correlation between template 2 and other templates. To determine the accuracy of the proposed model, two parameters that are accepted in various works are calculated. FAR and FRR, where FAR represents the frequency of inaccurate positive matching of the query image with obtained database, and FRR describes the frequency of rejection of the query image which is matching with one of the images from the database. Figure 7 compares the FAR and FRR. An equal error rate (EER) value of 12.1% is achieved at the normalized threshold value of 0.27. This demonstrates that the proposed model is capable of identifying the individual with higher accuracy with proper selection of the threshold value.

Table 2 summarizes the performance comparison of the proposed model with different models. The EER of the proposed model is comparable. Jazzar and Muhammad utilized the Zernike moments to extract the feature sets from fingerprint and palmprint images having a low resolution. F-ratio (Fisher’s ratio) is used to select the optimum fused feature sets. As discussed in Sec. 3.4, for better accuracy, higher moments of Zernike are required. Karki and Selvi proposed the multimodal biometric fusion method with three modalities. They utilized a curvelet to extract the features from the modalities. However, the dimensions of the feature sets obtained using the curvelet are very large. Therefore, two approaches based on PCA and significant feature extraction methods were used to reduce the size of the feature vectors to 1258. In the proposed model, a 10 bin histogram is utilized as the feature vector. Chin et al. proposed the Gabor filter-based fingerprint and palmprint features fusion at the feature level. Then a random tiling method is used to extract the features from fused images. The disadvantage of the Gabor filter is its redundancy.

6 Conclusion

The unimodal biometric system is vulnerable to various threats. The paper proposes the multimodal biometric recognition model. By analyzing the characteristics of various modalities, it is found that the fusion of palmprint and fingerprint features-based algorithms yields a higher accuracy. The histogram of a Radon-based feature extraction model is utilized. To make the model invariant to scaling, the logarithm of the histogram is calculated. The Radon transform is sensitive to rotation. Therefore, a correlation is obtained for each rotated modality and the maximum correlation value gives the identification of the individual which is invariant to the rotation. The fusion of palmprint and fingerprint is done at the decision level. The proposed model fused the unique characteristics of palmprint and fingerprint for identification. The EER can be further decreased when more unique features are extracted.

A demo MATLAB® implementation to generate the feature vector templates of the datasets is given below.

1. Program for reading datasets and fusion of feature vectors

```matlab
fingerprint_pathname = uigetdir('
', 'Select Training Fingerprint...
Dataset'); % Fingerprint Dataset path
files = dir(fingerprint_pathname);
handles.fingerprint_pathname = fingerprint_pathname;
fingerprint_feature_vector=training_tst...
hst_fun...
(fingerprint_pathname, files);
```

Fig. 6 Correlation between the feature set of same individual and another individual.

Fig. 7 FAR versus FRR graph to see the accuracy of the proposed model.

<table>
<thead>
<tr>
<th>Reference</th>
<th>Biometric identity</th>
<th>EER (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jazzar and Muhammad</td>
<td>Fingerprint and palmprint without F-ratio</td>
<td>14.54</td>
</tr>
<tr>
<td></td>
<td>Fingerprint and palmprint with F-ratio</td>
<td>13.80</td>
</tr>
<tr>
<td>Karki and Selvi</td>
<td>Fingerprint, face and signature (extracting significant coefficients)</td>
<td>22.35</td>
</tr>
<tr>
<td></td>
<td>Fingerprint, face and signature (PCA)</td>
<td>5.32</td>
</tr>
<tr>
<td>Chin et al.</td>
<td>Fingerprint and palmprint (random tiling + 2N discretization)</td>
<td>11.09</td>
</tr>
<tr>
<td>Proposed model</td>
<td>Finger print and palmprint</td>
<td>12.10</td>
</tr>
</tbody>
</table>

Table 2 Performance summary of different fusion-based algorithms.
handles.training_finger_hst = fingerprint_feature_vector;
% Read palm print database and generate feature vector
palmprint_pathname = uigetdir(['','Select Training Palmprint... Dataset']);
% Palmprint Dataset path
files = dir(palmprint_pathname);
handles.palmprint_pathname = palmprint_pathname;
palmprint_feature_vector = training_hst_fun(palmprint_pathname,...
files);
handles.training_palm_hst = palmprint_feature_vector;
% Fusion of dataset for training images
training_palm_hst1 = handles.training_palm_hst;
training_finger_hst1 = handles.
training_finger_hst;
sz = size(training_palm_hst1);
for i= 1:sz(2)
  palm = training_palm_hst1{1,i};
  finger = training_finger_hst1{1,i};
  training_fusion{i} = horzcat(palm,
  finger);
end
handles.training_fusion = training_fusion;
% reading test fingerprint and palmprint
[imname,pathname]= uigetfile('*.tif','
Select Test Fingerprint...
Image');
full_path = strcat(pathname,'\',
imname);
ii = strfind(imname,'.');
imindex = imname(1:ii-1);
fingerprint_feature_vector = training_hst_fun(pathname,
full_path);
handles.test_fingerprint_hst =
fingerprint_feature_vector;
= uigetfile('*.bmp','Select Test Palmprint...
Image');
full_path = strcat(pathname,'\',
imname);
ii = strfind(imname,'.');
imindex_palm = imname(1:ii-1);
if strcmp(imindex,imindex_palm)
handles.test_full_path = full_path;
else
  msgbox('Incorrect Palmprint
Selection, TRY AGAIN');
end
handles.palm_full_path = full_path;
palm_full_path = handles.palm_full_path;
palmprint_feature_vector=training_hst_fun(pathname, full_path);
handles.test_palm_hst = palmprint_feature_vector;
test_palm_hst = handles.test_palm_hst;
test_fingerprint_hst = handles.test_
fingerprint_hst;
test_fused = horzcat(test_palm_hst,
test_fingerprint_hst);
handles.test_fused_hst = test_fused;
% Template Matching
fingerprint_pathname = handles.
fingerprint_pathname;
palmprint_pathname = handles.palmprint_pathname;
test_fused_hst = handles.test_fused_hst;
training_fusion = handles.training_fusion;
test_inverse_fourier = test_fused_hst;
sz = size(test_fusion);
for i=1:sz(2)
  temp= training_fusion(1,i);
  temp = temp;
  distt{i} = sum(diag(hist_cost_2
  (temp,test_inverse_fourier)));
end
[val,ind] = min(cell2mat(distt));
if val==0
disp('Images are authenticated');
disp('Recognised Fingerprint Image');
disp('Recognised Palmprint Image');
else
  disp('Images are NOT authenticated');
end
2. Program to generate feature vectors
function fingerprint_feature_vector =
training_hst_fun...
(path, files)
fingerprint_pathname = path;
sz = size(files);
if sz(1) ~= 1
for i= 1:sz(1)-2
  imname = files(i+2).name;
  ind = strfind(imname,'.');
  ind= str2num(imname(1:ind-1));
  fullpath = strcat(fingerprint_pathname,
  '\',imname);
  im = imread(fullpath);
  I = mat2gray(im);
  BW = edge(I);
  theta = 0:179;
  [R, xp] = radon(BW,theta);
  R= log10(R); %Logarithm of Radon
  training_hst{ind} = hist(R);
end
fingerprint_feature_vector = training_hst;
% Calculate Radon transform of fingerprint
% calculation of histogram of logarithm Radon
% %
end

3. Program for matching feature vectors

function HC=hist_cost_2(BH1,BH2);
[nsamp1,nbins]=size(BH1);
[namp2,nbins]=size(BH2);
BH1n=BH1./repmat(sum(BH1,2)+eps, [nsamp1,nbins]);
BH2n=BH2./repmat(sum(BH2,2)+eps, [n1nbins]);
tmp1=repmat(permute(BH1n,[1 3 2]), [n1nbins 1 1]);
tmp2=repmat(permute(BH2n’, [3 2 1]), [namp2 1]);
HC=0.5*sum((tmp1-tmp2).^2)./(tmp1+tmp2+eps),3);

References


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Singularity Points Detection in Fingerprint Images

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ABSTRACT
An efficient algorithm for singular points (core and delta) detection in fingerprint images is proposed. The algorithm is based on an efficient maximum variation in local orientation field calculation method. The method was tested with FVC-2000 fingerprint database and the results were compared visually to the results obtained by human experts. The algorithm is capable of detecting singular points with precision and less computational time. The proposed algorithm outperforms existing algorithms in detection accuracy and calculation speed.

Keywords
Fingerprint, orientation field, singularity points.

1. INTRODUCTION
Fingerprints are considered one of the most reliable biological characteristics for personal identification because of its stability and uniqueness. In general, an automatic fingerprint identification system includes five main stages: segmentation, enhancement, feature extraction, classification and matching. The identification of a person requires a comparison of his fingerprint with all the fingerprints in a database. This database may be very large (e.g., several million fingerprints) as in many forensic and civilian applications. In such cases, the identification typically has an unacceptably long response time. The identification process can be speeded up by reducing the number of comparisons that are required to be performed. A common strategy to achieve this is to divide the fingerprint database into a number of classes.

The detection of the singular points (cores and deltas) is an important and difficult task in automatic fingerprint classification and identification. Moreover, fingerprint images often contain noise, which makes the classification task even more difficult. Core points are the points where the innermost ridge loops are at their steepest. Delta points are the points from which three patterns deviate. Qi Yuan[1] utilized core position for direction registration and A K Jain, Prabhakar S et. al [2] utilized it for image adjustment. These adjustments reduce the influence of displacement on the image and increase the accuracy of the recognition system. The number of cores and deltas and the relative position between these points can be used for fingerprint classification and recognition [3, 4, 5, 6, 7, 8, 9, 10, 11, 12] thus improving the robustness of the system in presence of changes introduced by displacement and rotation on the image. The problem of singular points detection in fingerprint images has been addressed before by different authors. Construction of several templates for fingerprint images is proposed. The algorithm is based on an efficient maximum variation in local orientation field calculation method. The method was tested with FVC-2000 fingerprint database and the results were compared visually to the results obtained by human experts. The algorithm is capable of detecting singular points with precision and less computational time. The proposed algorithm outperforms existing algorithms in detection accuracy and calculation speed.

2. PROPOSED ALGORITHM
The proposed algorithm computes the core and delta points on the fingerprint image based on the maximum variation of its local orientation field. The method was tested with FVC-2000 fingerprint database and the results were compared visually to the results obtained by human experts. The algorithm is capable of detecting singular points with precision and less computational time. The proposed algorithm outperforms existing algorithms in detection accuracy and calculation speed.

In this paper a process for detection of singularity points based on maximum variation in local orientation field is introduced. Section II describes the proposed algorithm for detecting core and delta points. Section III displays the results and a brief discussion is carried out based on these results.
the gradient operator may vary from the simple Sobel operator to the more complex Marr-Hildreth operator.

Estimate the local orientation of each block centered at pixel \((i, j)\) using

\[
o(i, j) = \frac{1}{2} \tan^{-1} \left( \frac{V_y(i, j)}{V_x(i, j)} \right)
\]

where,

\[
V_x(i, j) = \sum_{u=-4}^{i+4} \sum_{v=-4}^{j+4} 2 \partial_x(u, v) \partial_y(u, v)
\]

\[
V_y(i, j) = \sum_{u=-4}^{i+4} \sum_{v=-4}^{j+4} \left( \partial_y^2(u, v) - \partial_x^2(u, v) \right)
\]

The value of \(o(i, j)\) is least square estimate of the local ridge orientation in the block centered at pixel \((i, j)\). Mathematically, it represents the direction that is orthogonal to the dominant direction of the Fourier spectrum of the \(8 \times 8\) window.

Convert the orientation field in to range of 0 to 180 degree.

\[
o(i, j) = \begin{cases} o(i, j) & \text{if } o(i, j) < \pi \\ \pi + o(i, j) & \text{if } o(i, j) \leq -\pi/2 \\ o(i, j) - \pi & \text{otherwise} \end{cases}
\]

Smooth the orientation field in a local neighborhood. In order to perform smoothing (low pass filtering), the orientation image needs to be converted into a continuous vector field, which is defined as

\[
\phi_x(i, j) = \cos \left( 2o(i, j) \right)
\]

and

\[
\phi_y(i, j) = \sin \left( 2o(i, j) \right)
\]

where, \(\phi_x\) and \(\phi_y\) are the \(x\) and \(y\) components of the vector field, respectively. With the resulting vector field, the low pass filtering can be performed as

\[
\phi_x(i, j) = \sum_{u=-w/2}^{w/2} \sum_{v=-w/2}^{w/2} W(u, v) \phi_x(i - wu, j - wv)
\]

and

\[
\phi_y(i, j) = \sum_{u=-w/2}^{w/2} \sum_{v=-w/2}^{w/2} W(u, v) \phi_y(i - wu, j - wv)
\]

where \(W(\cdot)\) is a two dimensional low pass filter with unit integral and \(W \times W\) specifies the filter size. Note that smoothing operation is performed at the block level. For our experimentation we have used a \(5 \times 5\) mean filter. The smooth orientation field \(O\) at \((i, j)\) is computed as

\[
O(i, j) = \frac{1}{2} \tan^{-1} \left( \frac{\phi_y(i, j)}{\phi_x(i, j)} \right)
\]

Extract the part of image having maximum variation in intensity using mask of size \(3 \times 3\).

Thin the image.

The singularity detected is referred as delta if the pixel below the singularity point is having angle less than 60° in the orientation field, otherwise it is referred as core.

Figure 1 shows the complete process of obtaining the singularity points based on the local field orientation. Figure 1(a) and (b) are obtained by computing the gradient \(\partial_x(i, j)\) and gradient \(\partial_y(i, j)\) respectively. The local orientation for each block is calculated using (1) to obtain Figure 1(e). The Local orientation field 0°–360° obtained in Figure 1(e) is converted to 0°–180° using (4) as shown in Figure 1(f). The orientation image is converted into a continuous vector field by (5) and (6) to obtain \(X\) component of continuous vector field as shown in Figure 1(g) and \(Y\) component of continuous vector field as shown in Figure 1(h). Smoothing of image is carried out using (9) to obtain Figure 1(i). The part of image having maximum variation of intensities is extracted using mask of size \(3 \times 3\) to obtain Figure 1(j). This figure is then thinned using thinning algorithm to obtain a line joining the singularity points as shown in Figure 1(k). The detected singularity points can be seen in Figure 1(l). The proposed algorithm is implemented on various classes of fingerprints.
Figure 1 Various steps explaining the proposed algorithm (a) gradient \( \partial_x (i, j) \) (b) gradient \( \partial_y (i, j) \) (c) \( V_x (i, j) \) (d) \( V_y (i, j) \) (e) Local orientation field \( 0^\circ - 360^\circ \) (f) Local orientation field \( 0^\circ - 180^\circ \) (g) \( x \) component of continuous vector field (h) \( y \) component of continuous vector field (i) smoothened orientation field (j) extracted area of max variation in local orientation (k) Thinning of maximum variation in local orientation image (l) Detected singularity points shown on the original fingerprint image.
Figure 2 shows each class of fingerprint along with their detected singularity points and the maximum variation in local orientation field.

3. RESULTS AND DISCUSSION

The algorithm was executed using MATLAB version 6.3 on a P-IV, 1.2 GHz computer. Randomly selected fingerprint images containing noise, different scale and orientations from the FVC 2000 database is used for detection of singularity points. As per the FVC-2000 specifications the fingerprints were acquired by using a low-cost capacitive sensor. The average time taken for executing the algorithm for detection of singularity points is 2.36 seconds. As the singularity points are being extracted from the orientation field it makes the output highly noise tolerant. Figure 3 displays a set of fingerprints chosen from the FVC-2000 database.

![Legend](image1)

(a)

(b)

(c)

(d)

(e)

Figure 2 Singularity points for various classes of fingerprints along with the maximum variation of local orientation field image.

Each group of fingerprints consist of eight images of the same class namely Arch, Left loop, Right loop, Whorl and Twin loop. The core and delta points have been distinctively marked. Test results were obtained by comparing the singular points extracted by the proposed algorithm to the singular points detected by human experts. Results were also compared with other singular point detection algorithms. In [26], problems are observed with the whorl type of fingerprints and images with extremely steep ridge curves. Also obtained core points seemed to consistently move away from the actual core points. In the proposed algorithm the points are exactly and consistently found at the precise position. The average calculation time for the algorithm in [3] is 7.8 seconds and for the proposed algorithm is 2.36 seconds under similar conditions. Results show that the detection accuracy is better as compared to the previous algorithms. Consistent results are achieved irrespective of classes of fingerprints, their position, scale, rotation and noise.
The performance of the algorithm has been also evaluated using the Receiver Operating Characteristics (ROC). This consists of a measure of false acceptance rate (FAR) and the false rejection rate (FRR) at various thresholds. Alternately the Genuine acceptance rate (1-FRR) and FAR may be measured at different thresholds. A genuine matching score is obtained when two feature vectors of the same individual are compared and an imposter matching score is obtained when feature vectors of two different individuals are compared. A single template per subject has been considered for experimentation. For every possible combination the algorithm has been tested for computation of FAR and FRR as shown in Figure 4.

4. CONCLUSIONS

A novel approach towards singularity points detection based on the maximum variation in local orientation field of fingerprint image has been proposed. Accurate and consistent singularity points detection greatly reduces fingerprint-matching time and computational complexity for a large database. It is a sophisticated and accurate method for detection of core and delta points and is highly noise tolerant. The proposed algorithm produce better results at lower and higher values of FAR as compared to minutiae based algorithms. As the algorithm takes fewer computations it could be implemented using the real time processor.
Figure 4 Performance evaluation of the proposed algorithm based on singularity points.

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FEATURE EXTRACTION USING HISTOGRAM OF RADON TRANSFORM FOR PALMPRINT MATCHING

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ABSTRACT

This paper presents principle line based palm print matching model as principle lines are easily extracted in even in low resolution images. This paper proposes use of histogram of Radon transform (HRT) to extract the features of palm. However the HRT is sensitive to the rotation and scaling due to normalization process. Therefore here logarithm is employed while discarding the normalization process and its histogram is utilized as feature vector. To compare the palm prints, the calculation of correlation coefficient of this logarithm histogram is proposed in the paper. The proposed model is applied to polyU database and results are analyzed in terms of receiver operating characteristic.

KEYWORDS: Palmprint, Matching, Radon Transform, Histogram

I. INTRODUCTION

Biometric plays major role to get one’s identity. One of the example of biometric are fingerprint [1] as it is hardly possible to find the similar fingerprint for any two individuals. One of the crucial properties required for identity is inimitability. Other equally important aspect is being present in all individuals for life time. They must be easy to extract. Similar biometric characteristics are iris, palm, retinal structure, face and handwriting. Out of these, palm based identification have been intensively developed because of its crucial advantage over other features.

Palm region can be identified even in low resolution images. In such cases, the distinguishable features rely on palm lines and textures patterns. High resolution image also contains ridges and wrinkles which can be utilized as classification and matching features. The main objective of this paper is to proposed identification system based on palm print feature matching.

Different palm print methods can be been classified according to the process they utilized. Preprocessing step involves the cropping of region of interest (ROI) form hand geometry. Second step involves the feature extraction method. Third step is feature reduction from extracted features and finally classification step is involved for individual’s identity. Numbers of algorithms have been proposed using different combination of each of above defined stage like in [2], wavelet based line orientation information are extracted. Along with orientation, energy of sub bands also has been utilized to describe the palm. Zernike moments based feature extraction method was proposed by Pang et al. [3], where higher order moments were compared for identification. Feature extraction method associated with its spatial location exhibit better performance, i.e. principle line based approach. In most of the method, the ROI is cropped [4, 5] and corresponding feature extraction is
performed on ROI. If the coordinate systems are well aligned for different images then corresponding to palm area, comparison between the feature vectors is meaning full with regards to spatial information. Present approach in this paper utilized ROI area from aligned palm print images along same coordinate system. To extract the principle lines, wavelet and directional context modeling based algorithm was proposed in [6]. Similarly integration of kernel based edge detection and morphological model also have been proposed in [7]. Similarly, H B Kekre et.al [20] presented the efficiency of various wavelet transform for palm print recognition. Other wavelet based model can be find in [17, 18]. In both the model, the features size is large and it needs to be reduced. Radon transformation has been utilized in [8] to extract the principle lines. In [8], a filter based approach based on Radon transform is implemented to detect lines. Superposition is used to match palmprints. In [22], Wei Jei et.al proposed a novel orientation based scheme, in which three strategies, the modified finite Radon transform, enlarged training set and pixel to area matching, have been designed to further improve its performance. In [21], author proposed the local binary pattern (LBP) based model where LBP descriptor is applied to the energy or direction representation of palmprint extracted by MFRAT.

As principle lines are most robust and unique features and due to easiness in extraction from ROI, this paper also present line extraction based model for palmprint matching. In this paper, palm print database from polyU [16] is utilized which provides the extracted palm ROI from the hand. Thus paper is more devoted to the palm print matching than the extraction of ROI. In all literature the radon transform is combined with other model and then similarity model is employed in terms of Euclidean distance. While this paper presents a novel approach to characterize the palmprint using histogram of radon transforms only. The histogram of radon (HRT) is widely utilized to represent the shape of an object [10]. This is most robust toward the scaling and rotation of object. Therefore this paper proposed a model to extract the rotation and scaling invariant feature extraction method using HRT.

Rest of paper is organized as follows: Section-II discusses the proposed model implementation where first part is explain the histogram of Radon based feature extraction method and second part explain the matching process. Based on that in section-III corresponding results are explain and accuracy of model is presented in term of false acceptance and false rejection ration. Finally conclusion and feature work is proposed related to proposed model.

II. PROPOSED MODEL

2.1 Radon transform based lines’ feature extraction:

In palm ROI, the principle lines can be considered as a straight line. To extract the straight lines radon [19] is widely utilized as it is able to transform two dimensional lines into possible line parameter. Thus each line in the 2-D domain generates maximum value at the corresponding line parameters in radon domain. Another strong capability of radon transform is able to extract the lines from vary noisy environment. Another useful property of radon is that each peak in radon domain reflects the value of individual lines. i.e. from the radon transform shown in figure 1(b), the crossing lines makes no problem in separation of peaks.

![Figure 1: Image having cross lines and corresponding radon transform.](image-url)
Based on that so many algorithms [9-11] have been presented to extract the palm features using radon transform. Thus in [10], finite radon transform is applied to extract the lines features and wavelet transform is utilized to extract the corresponding point from radon domain. Similarly in [11] the author modified the radon transform with consideration of energy and direction to extract the palm lines. In [12], modified radon transform is utilized along with iterative closet point method for line based feature extraction. Thus in all radon based approach, the radon domain is integrated with other model to extract the features. In this paper, use of histogram of radon domain is proposed to extract the lines features.

2.2 Feature extraction using histogram of radon transform:

Presently histogram of radon transform (HRT) plays vital role in shape analysis as introduced by S. Tabbone [13]. The HRT represents the shape length at each orientation. It is also translation and rotation invariant. Thus HRT gives similar response to the palm having either rotation or translation. This is the most advantage in compared to finite radon or modified radon transforms presented [11, 12].

In [13], normalization of radon image and histogram is utilized to achieve scaling invariance. This is highly sensitive to the noise. Therefore in [14] logarithm conversion and phase correlation is utilized by avoiding the normalization process. This LHRT (logarithm HRT) is invariant to the noise.

Therefore this paper utilized this property to extract the features of palm lines using LHRT.

Let I(x,y) be an binary image (after extraction of palm ROI). Its radon transform is defined as:

\[
R(\theta, \sigma) = \int \int I(x, y) \delta(x \cos \theta + y \sin \theta - \rho) dx dy
\]  

Where \( \delta(\cdot) \) is Dirac delta function, \( \theta \in [0, 2\pi] \) and \( \sigma = [-A/2, A/2] \), A is the size of image diagonal. Thus radon gives summation over the line defined at angle \( \theta \). The radon transforms are shown in figure 1. Then logarithm is applied on equation 1.

\[
R_f(\theta, \sigma) = \ln R(\theta, \sigma)
\]  

Corresponding HRT is calculated as

\[
LHRT(\theta, y) = H(R_f(\theta, \cdot))(y)
\]

Where \( H \) is histogram of radon in direction \( \theta \). During the calculation of H normalization process is avoided to make it translation and rotation invariant.

The features of palm are obtained by calculating the phase correlation of the obtained LHRT. Where the Fourier transform of LHRT is calculated and corresponding correlation function is calculated for the identification process. The detail of matching process is explained in coming section.

2.3 Palm Matching:

To match the two images, phase correlation [14] is utilized. The correlation function is defined as:

\[
C = \sum G(u,v)_1 \ast G(u,v)_2
\]

Where \( G(u,v) \) is inverse Fourier transform of LHRT, subscript 1 indicate query palm image features and 2 indicates palm features from the database. To match two palms, this correlation function is compared with specified threshold. If \( C \) is higher than the defined threshold then we can say that two palms are same.

III. EXPERIMENTAL RESULTS AND DISCUSSION

To evaluate the performance, Polyu [16] database is utilized, which provide palm images. For local hand images, it is required to extract the ROI (palm) and to correct the rotation. The proposed model have been implemented on Pentium – IV processor with 1GB RAM, 2.8 GHz PC under MATLAB.
environment. There are so many algorithms have been suggested in various literature surveys [14, 15]. To get the features, following steps are performed:

Step: 1 Calculate the radon coefficients.

Step: 2 Obtain the logarithm of radon coefficients.

Step: 3 Calculate histogram of radon coefficients.

Step: 4 for matching purpose calculate the correlation function using equation 4 and compare it with defined threshold.

As shown in figure 2, palms images of two persons are shown, where first row shows the palm images of single person having variation in intensities, containing noise and small rotation. Similarly second row is the palms images for another person.

![Figure 2 Palm images from utilized database](image)

The proposed model is executed using MATLAB version 6.3 on P-IV, 1.2 GHz computer. As earlier said, radon transform is obtained on binary image of palm. Binary image of palm gives principle line. As discussed in section 1, in most of radon based model, the radon coefficients are combined with other features. While proposed model requires calculation of histogram only and obtained histogram is utilized as feature vector for comparison. The performance of model is tested on 30 X 4 palm images, where 4 images are of single person.

The following table shows the comparison of palm image with each other. In table 1, it can be seen that when palm image 1 is compared with its sub images, correlation coefficients values is nearer to 98, while the correlation coefficients for palm image 1 with other palm image is less than 97.

<table>
<thead>
<tr>
<th>Plam Image</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>100</td>
<td>98.24</td>
<td>98.43</td>
<td>98.29</td>
</tr>
<tr>
<td>2</td>
<td>95.24</td>
<td>94.86</td>
<td>95.27</td>
<td>95.26</td>
</tr>
<tr>
<td>3</td>
<td>96.38</td>
<td>95.77</td>
<td>95.25</td>
<td>95.28</td>
</tr>
<tr>
<td>4</td>
<td>96.30</td>
<td>95.91</td>
<td>95.85</td>
<td>95.85</td>
</tr>
</tbody>
</table>

This performance is evaluated using receiver operating characteristic. This consists of false rejection rate and false acceptance rate. These FAR and FRR can be measured at different threshold. For every possible combination the model has been tested to calculate FAR and FRR as shown in figure 3.
IV. CONCLUSION AND FUTURE WORK

Novel approach for palmprint matching is proposed in this paper. The proposed model is based on principle line as this principle line can be easily extracted even in low resolution images. This principle lines can be considered as small lines therefore radon transform is utilized which have capability of extracting lines even in noisy and overlapping lines images. The histogram of radon is not much utilized as a feature vector generation and less attention is given in term of shape identification only. This paper proposed the use of HRT to extracts the features of palm lines. Again to make histogram scale and rotation invariant, normalization is avoided and logarithm is calculate before histogram calculation as suggested in [14]. The performance evolution in terms of receiver operating characteristic is obtained to shows the accuracy of proposed model. Again in compared to other radon based model, the proposed model is computational less as it requires calculation of radon coefficients and its histogram. The proposed model gives promising result but still it requires computation of accuracy by comparing the proposed model with other radon based model. Similarly in proposed model, extraction of radon coefficients is highly sensitive to the principle line identified in spatial domain. So the proposed model can be integrated with the model which is able to extract the principle line in more robust way.

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Abstract—This paper presents comparative study of palmprint matching algorithms for low resolution and noisy images. The principal lines and wrinkles are the only features easily extractable under low resolution. Therefore widely used Radon based approach has been studied and presented in this paper. Based on the computational complexity and fast matching, four different approaches are studied.

Keywords—Radon Transform, palmprint identification, Delaunay Triangulation.

I. INTRODUCTION

Biometrics is person identification on the basis of exclusive physiological and behavioral features. Biometrics has almost replaced other means of authentication like passwords and keys. Biometric modalities are more reliable than the passwords. The passwords can be forgotten or hacked where as keys can be lost. The individual’s unique physiological or behavioral characteristics, on the other hand, are hard to forged or lost. Finger print and face are the most commonly used biometrics nowadays, but they have inherent problems. The performance of face recognition algorithms is affected by illumination variations. The finger print has less user acceptability due to the historical use in crime investigations. Palm print is a biometric modality which has recently drawn great attention owing to its strengths like ease of acquisition, robustness, user acceptance in addition to its uniqueness and rich distinguishable contents and features. Palm print offers widely discernible and discriminating features. These features are consisting of principal lines, ridges and wrinkles, singular point, and minutiae point and textures patterns. Out of these principal lines and wrinkles can be easily extracted even in low resolution images.

Palmprint verification/identification approaches can be categorized as follow:

A. Texture Based Approach

Texture features are extracted using 2-D Gabor filter in Palmcodes method. This approach achieved good performance in terms of high processing speed and accuracy [1]. David Zhang et al extracted the phase information using multiple elliptical Gabor filters with different orientations [2]. The texture energy concept is utilized to define the features of palmprint images.[3] Texture energies of palmprints are extracted using dual-tree complex wavelets[4].

The limitation of Gabor filter is selection of parameters. The Gabor filter is highly sensitive to the parameters like its variance, frequency and angle of orientation. Therefore to achieve high accuracy, it requires combination of different features from the large number of orientation with different scales which limits the speed of processing.

B. Appearance Based Approach

Appearance based approaches produces interesting results. Principal component analysis (PCA) based approach is proposed by Lu et al.[12]. Wu et al proposed Linear Discriminant Analysis (LDA) approach [13]. T Connie et al focused on principal component analysis (PCA), fisher discriminant analysis (FDA) and independent component analysis (ICA).They adopted wavelet transform in order to analyze the palmprint images in multi-resolution-multi-frequency representation [14]. Two dimensional Locality preserving projections (2D-LPP) utilized by Hu et al and unsupervised discriminant projections(UDP)proposed by Yang, produces satisfying results[15,16]. It is possible that these results may be sensitive to illumination, contrast and position change.

C. Orientation Based Approach

Orientation features contains more information than any other feature also it is insensitive to illumination changes. Hence orientation based approach is considered to have best performance in palmprint matching. Kong and Zhang [17] investigated orientation information of palm lines for palmprint matching. It is also defined as Competitive code. Another feature based approach which gives the orientation of each pixel uses several directional filters[18]. Orientation features for palmprint matching were also used in Ordinal code and Robust Orientation Code proposed by Sun et al and Jia respectively[19,20]. In summary, orientation features based model requires use of directional filters and hence accuracy of algorithms depends on the selection of number of directional
filters. The design of optimum directional filter is an issue. The orientations features cannot be identified in low resolution images.

D. Line Based Approach

Principal lines and wrinkles from the palmprint are also utilized as features for identification. Zhang and Zhang [5] used line based approach to detect principal lines and wrinkles. They extracted these features using image transformation into wavelet domain and directional context modeling technique. Sobel’s and morphological operations are utilized to extract the line like features from the palm images [6]. However with these methods the palm lines cannot be explicitly extracted. Palm lines are considered as wide lines and extracted [7-8]. Directional and multiresolution decomposition is applied to extract the palmprint features by Lin et al [9]. Wu et al considered the palm lines as roof edges. They extracted the edges in accordance with zero cross point of the image’s first order derivative and the magnitude of the edge’s point [10-11].

In comparison the above said features, the extraction of principal lines and wrinkles are easy and fast. These features are most visible and stable. These features are less sensitive to the image resolution and noise. The time required for matching using principal lines based approach is very less in comparison to other features based palmprint matching models. Therefore this paper presents the comparative study of models based on principal lines and wrinkle extraction. The principal lines are defined as heart line, head line and life lines. These lines are most visible in the palmprint. To separate out the principal lines from the wrinkles, the line energy and direction vectors are utilized. Line energy is always stronger for principal lines in comparison to wrinkles. Since Radon transform is powerful to detect both line energy and direction in this paper Radon transform based approach is presented.

II. FEATURE EXTRACTION BASED ON RADON TRANSFORM

The Radon transform of 2D function can be defined as

\[ R(r, \theta)[f(x, y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) \delta(r - x \cos \theta - y \sin \theta) dx dy \]  

Where \( r \) is distance of lines from the origin and \( \theta \) is the angle between the line and y-axis. Radon transform is effectively utilized to detect the lines. However it cannot detect the line segments which are significantly shorter than the image dimension. In order to eliminate this effect, modified Radon transform (MFRT) based palmprint verification had been proposed in [21]. In this transformation, the energy and direction are calculated at each pixel. These energy and directions are utilized to extract the principal lines. He shown the comparison of MFRT model with Gabor based approach with better ROC characteristic. From the results it can analyzed that radon based approach extracts the principal lines from complex palmprint images easily and effectively. Verification results show the strong ability of discrimination of palmprint using principal lines. Even though computational complexity of MFRT is less in comparison to Gabor filter based approach, the MFRT is time consuming approach as it requires calculation of energy and direction at every pixels [22].

A new approach to characterize the features of palmprint is defined by the topological structure of palm where the main feature points calculated by Radon transform are connected using Delaunay triangulation. To obtain the Delaunay triangle, they obtained the Vernoi diagram which decomposed the space into polygonal region and using vernoi diagram, Delaunay triangle is formed.

Fig 1 (a) Original Palm, (b) R(LA_image), (c) Thinning Lines

Similarity between two palmprint is obtained by calculating Hausdorff distance. This model is robust towards the noise. Because of topological structure this model is more stable and robust to the noise. However this model is also sensitive to the extraction of radon coefficients.

Presently radon histogram is utilized for shape analysis which represents the shape lengths at each orientation. The
palmprint identification requires rotation invariant features for better accuracy. The histogram of radon transform has advantage that it gives identical response for the palm having rotation and translation. Based on that palmprint principal lines are extracted using histogram of radon transform (HRT) in [24]. HRT is defined with respect to orientation as

\[ L_{HRT}(\theta, y) = H(R_f(\theta, \cdot))(y) \]  

(2)

Where \( H \) is histogram of radon in direction \( \theta \)

To identify the palmprint, phase correlation of obtained LHRT is utilized. Demonstrated results are comparable with MFRT based model. It is analyzed that in the HRT based model, only histogram is need to be calculated and it provides rotation and translation invariant features. Therefore overall computation time is less in comparison to MFRT based approach. In contrast, extraction of radon coefficients is highly sensitive to the principal lines identified in spatial domain.

In Delaunay triangle based approach, Vornoi diagram is utilized to form polygonal structure. Another computation less approach related to Delaunay triangle has been presented in [25] where polygon region is formed in spatial domain using Radon coefficients and their area and periphery are utilized as palmprint features for identification. To form the polygon, the outermost pixels related to radon peaks are utilized. Palmprint matching is done using calculation of hamming distance between the area and periphery. This is most computational less approach as it requires formation of polygon only and because of less feature vector size, identification of palmprint is fast in comparison to other radon based approaches.

Fig: 2(a) Original Palm, (b) Radon transform of ROI, (c)Delaunay triangle representation of palmprint

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This paper presents the comparative study of palmprint matching using Radon based transformation technique. Radon based approach extracts the principal lines and wrinkles as features. The radon based approach has advantage that it can detects these features even in low resolution images and it has less computational complexity in comparison to other feature extraction models. In this paper, establish the comparison between four radon based models: MFRT, Delaunay triangle formulation method, polygon formulation model and histogram of radon based model. It is found that except MFRT, all three methods are sensitive to the extraction of radon coefficients. Overall radon based approach is fast. However in all models, only principal lines are utilized as features point. In features integration of other features can be done with principal lines to improve the accuracy of models.

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REFERENCES
Computation Less Radon Based Palmprint Characterization

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Abstract

Palm based biometric based individual identification is proposed in this paper as palmprint recognition can be done in low resolution images and contains significant unique features. In this paper, principle line based approach is presented as principle line extraction is easy as compared to other ridge and valley and minutia point detection. Here radon based approach is presented for palm feature point extraction and matching. From the radon coefficients, the corresponding points in spatial domain are identified. From obtained points, using outlier points, polygon is formed. The area and periphery of obtained polygon are utilized as feature vector for matching purpose. Results on polyU database concludes that proposed model is efficient and has less computational complexity as compared to Gabor and other radon based model.

Keywords: Biometric, Palmprint identification, Radon transform, Polygon.

1. Introduction

Biometrics is an evolving component in today’s world used almost everywhere for security and personal identification. The purpose of biometric is to identify an individual through physiological features. These physiological features can be obtained based on fingerprints, hand geometry, iris pattern and face. The major characteristic of any physiological feature are need of uniqueness and not susceptible to any attack. Within this context, palm print have several advantage in compared to other like it can be identified even in low resolution images, it requires low capturing device and more ever one can extract number of features for the identification purpose. Therefore this paper proposed palm based physiology feature extraction method. In general any palm print matching model requires preprocessing of an image to obtain the region of interest (ROI) and for removal of noise. Then from ROI, unique features are extracted for the point of matching process. This matching is done by comparing the features with query image features.

Palmprint contains many unique features which are utilized for matching purpose. These features are consisting of principle lines, ridges and wrinkles, singular point, and minutiae point and textures patterns. Out of these principle lines and wrinkles can be easily extracted even in low resolution images with less than 100 dpi [24]. To extract the rest of features required high resolution images. Therefore this paper proposed a model based principle line features.
Different palm print methods can be been classified according to the process they utilized. Preprocessing step involves the cropping of region of interest (ROI) form hand geometry. Second step involves the feature extraction method. Third step is feature reduction from extracted features and finally classification step is involved for individual’s identity. Numbers of algorithms have been proposed using different combination of each of above defined stage like in [9], wavelet based line orientation information are extracted. Along with orientation, energy of sub bands also has been utilized to describe the palm. Zernike moments based feature extraction method was proposed by Pang et al. [28], where higher order moments were compared for identification. To extract the principle lines, various models have been proposed which includes Gabor based feature extraction [2, 6, 15, 17, 19, 20], Radon based extraction [11, 16] and wavelet based extraction [9], contourlet etc. The Gabor filter generates large number of features and having more redundancies. Therefore to reduce the feature size, Principle Component Analysis (PCA) [3], Fisher Discriminate Analysis [4], Independent Component Analysis (ICA) [5] are utilized along with Gabor. Based on that in [2] Gabor wavelet and 2-Dimensional (PCA) based algorithm was utilized for palmprint recognition and superior results were shown in compared to 1-D PCA. Gabor feature-based two-directional two-dimensional linear discriminate analysis was also proposed in [19] for palmprint recognition. Similarly in [19] principle lines orientation were analyzed using Gabor filter and utilized with competitive coding scheme for matching purpose. To find the orientation of each Gabor filter a modified fuzzy C-means cluster algorithm also was proposed in [17].

Wavelet transform is also utilized to extract the palmprint features. G Y Chen, W F Xie [7] had extracted the textural energy of palmprint using dual tree complex wavelet. Use of contourlet transform and non subsampled contourlet transform [23] is also proposed to extract the textural information of the palmprint.

Except this transformation techniques, other methods include discriminative local binary patterns statistic (DLBPS) based feature extraction [12], feature representation using Kernel Fisher Discriminant Analysis (KMDA) [13], two- dimensional locality preserving projections(2DLPP)[14], multiple orientation based characterization of local palm region using binary orientation co-occurrence vector (BOCV) [18], 2D Orthogonal filter[21] based texture and phase dependent feature extraction, the segment based matching and fusion algorithm[1].

Radon transform is also utilized to extract the features from palmprint. A modified Radon transform is used in [11] for feature extraction and pixel-to-area comparison formulated to match palmprint. Modified radon transform is utilized in robust online orientation code (RLOC) [16] to extract the orientation feature of palm. Radon transform and geometric Delaunay triangulation [22] were used to extract the directional characteristics and Hausdorff distance is used as criterion of similarity. The Radon transform extracts principal lines from the palmprint. And as earlier said, principle lines can be easily extracted even in low resolution images. Therefore this paper proposed the model based on radon transform.

2. Background
The 2D radon transform gives projection of image intensity along the oriented line at specific angle. The radon value at any arbitrary pixel location is obtained by integrals along the lines of all direction passing from that pixel. Thus radon transform maps linear signal components into pronounced extreme which can be detected very robustly. The coordinates of these peaks are reliable estimates of the geometrical parameters of collinear structures. In this paper, these peaks are identified and using that peaks feature matching algorithm is proposed to identify the palmprint.

Suppose a 2-D function $f(x,y)$ (Fig. 1). Integrating along the line, whose normal vector is in $\theta$ direction, results in the $g(s,\theta)$ function which is the projection of the 2D function $f(x,y)$ on the axis $s$ of $\theta$ direction. When $s$ is zero, the $g$ function has the value $g(0,\theta)$ which is obtained by the integration along the line passing the origin of $(x,y)$-coordinate. The points on the line whose normal vector is in $\theta$ direction and passes the origin of $(x,y)$-coordinate satisfy the equation:
\[
\frac{y}{x} = \tan(\theta + \frac{\pi}{2}) = -\frac{\cos \theta}{\sin \theta} \Rightarrow x \cos \theta + y \sin \theta = 0
\]

The integration along the line whose normal vector is in \( \theta \) direction and that passes the origin of \((x, y)\)-coordinate means the integration of \( f(x, y) \) only at the points satisfying the previous equation. With the help of the Dirac “function” \( \delta \), which is zero for every argument except to 0 and its integral is one, \( g(0, \theta) \) is expressed as [26]:

\[
g(0, \theta) = \iint f(x, y) \cdot \delta(x \cos \theta + y \sin \theta) \, dx \, dy
\]

Similarly, the line with normal vector in \( \theta \) direction and distance \( s \) from the origin is satisfying the following equation:

\[
(x - s \cdot \cos \theta) \cdot \cos \theta + (y - s \cdot \sin \theta) \cdot \sin \theta = 0 \Rightarrow x \cos \theta + y \sin \theta - s = 0
\]

So the general equation of the Radon transformation is defined as

\[
g(s, \theta) = \iint f(x, y) \cdot \delta(x \cos \theta + y \sin \theta - s) \, dx \, dy
\]

The inverse of Radon transform is calculated by the following equation:

\[
f(x, y) = \int_{-\frac{\pi}{2}}^{\frac{\pi}{2}} \rho \cdot R_{\theta}(s(x, y)) \, d\theta
\]

Where \( R_{\theta} \) is the Radon transformation, \( \rho \) is a filter and \( s(x, y) = x \cos \theta + y \sin \theta \)

**Figure 1:** The Radon Transform computation.

The properties of radon transform are:

1. It maps Cartesian into polar pixel coordinates and replace the complex search for aligned topologically connected clusters of pixels by the search of relative maxima in the transform image.
2. Each pixel of the transformed domain will be associated with a unique line in the original image. The larger the transformed image, the finer will be the granularity in the representation of lines in the original image.

Thus the extract the features from the palmprint, the proposed model relies on these two properties.
3. Proposed Method
3.1. Feature Extraction Based on Principle Lines

In palm ROI, the principle lines can be considered as straight lines. Therefore, the radon transform is applied to the palm ROI. Above said radon transform gives the number of peaks in the radon domain. The advantage of radon transform is ability to generate individual peak even for crossing lines. Therefore, crossing of two palm lines do not make any problem in separation of two peaks. That is shown in below figure 2. To extract the features point and reduce the size of features, here instead of all the peak points, set of peak points in descending order have been utilized. Once this peaks points are identified, based on the location of peaks point in radon domain, corresponding pixels have been identified in palm spatial domain. Let $g$ is an array consist of radon projection coefficients obtained along with 360° rotation period (See equation 4). Then the size of $g$ is $n \times 360$, where $n$ depends on the size of an image. From obtained radon coefficients, to reduce the feature vector size, maximum coefficients are obtained along each projection.

![Figure 2: Image having cross lines and corresponding radon transform.](image)

This can be written as

$$G_{sg}(\theta) = \max_s \{g(s, \theta)\} \quad (6)$$

Then we adopted limited set of radon coefficients for each palm print image. In this paper 33 radon coefficients are utilized. From the available coefficients $G$ (equation 6), the corresponding palm pixels in spatial domain is determined. Once these spatial positions are obtained, geometric relationship is established between these pixels to form the feature point. Here polygon is formed from the available spatial points and corresponding area and periphery are utilized as feature vector for matching purpose.

Corresponding points on palm image is obtained using following equations:

$$x = M / 2 + x_p \cos\left(\frac{G_x \pi}{180}\right) \quad (7)$$

$$y = N / 2 + y_p \cos\left(\frac{G_y \pi}{180}\right) \quad (8)$$

In order to measure the similarity between points, geometric attributes can be established between these points. In this paper, closed polygon is formed using outlier pixel related radon peaks and rest of pixels which lies inside this polygon is discarded. Once polygon is obtained, its area and periphery is calculated.

3.2. Feature Vector Generation and Palmprint Matching

To match the palm, it is required to compare the input palmprint image with the database to determine which image is similar to the input palmprint. Once the spatial points have been identified from radon coefficients; the polygon is established using outlier spatial points. Remaining points are discarded.
From the formed polygon, area and its peripheral are calculated. For images of each database, we formed the area and peripheral matrix corresponds to the image within database. To match the query image, the polygon area of query image is compared with database features matrix. Thus overall method requires calculation of outlier point of polygon. In Gabor based method, the size of feature points depends on number of orientation selected to design the Gabor filter therefore it generates too many features. Thus it requires PCA or ICA to reduce the feature size. While in proposed model, it needs calculation of points based on radon projection and to form the single polygon. Thus proposed model is computationally more simple in compared to Gabor based model. Similarly in [1], they need to calculate the Delaunay triangle. Again proposed model have less computational complexity in compared to [1].

4. Experiment Results and Discussion
To evaluate the performance, PolyU [27] database is utilized, which provide palm images. For local hand images, it is required to extract the ROI (palm) and to correct the rotation, there are so many algorithms have been suggested in various literature surveys [20, 22]. Then radon algorithm is applied on ROI of palm to obtain the radon coefficients. Following fig 3 shows the results of two palms from database.

**Figure 3 Left:** Original Palm, (Middle) Radon’s maximum coefficients (Right) Polygon formation from outlier points

![Image](image1.png)

In order to measure the similarity between two palms, the area and periphery of the polygon obtained from the query image is compared with the stored values in the database. Following fig 4 and fig 5 shows the area and periphery of 130 images for polyU database [27].

**Figure 4:** Polygon areas of various palms

![Image](image2.png)
Table 1 and Table 2 provide the results obtained from some of the palmprint showing that each palmprint have unique feature vector with in form of polygon area and periphery. When two palmprint match the resultant difference of area and periphery is zero. Thus in proposed model, only polygon calculation is required in compared to other model [1, 2 and 5]. Also the feature vector size require to compare the palm is only 1X 2 (i.e. area and periphery). Which is very less therefore it is very fast in terms of processing.

**Table 1:** Similarity Measurement Based in Area of Polygon

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**Table 2:** Similarity Measurement Based in Periphery of Polygon

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5. Conclusion
This paper presents a palm print matching model dependent on principle lines as principle lines can be extracted even in low resolution images. In this work we have presented a new model to extract the features of palmprint using Radon Transform. This Radon based approach extracts the invariant features from image. For that maximum radon coefficients values from Radon projection is utilized. As obtained Radon coefficients represent the points corresponds to the principle lines, these points location are obtained within palm images. From obtained palm points polygon is formed as a feature vector. To recognize the query image, the area and periphery of polygon obtained from query image are compared with those of database images. Small difference between these two feature vectors recognizes the image. Proposed model is applied to images from polyU [27] database. Results from table 1 shows that proposed model is accurate and computationally efficient in compared to Gabor based model and other radon based algorithm. For future work, the proposed technique can be improved by fusing each signature with other useful information such as hand texture.

References


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Subject: "IJAET :Paper: PALMPRINT MATCHING USING HISTOGRAM OF RADON TRANSFORM"

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**Paper Title:** Singularity Points Detection in Fingerprint Images

**Paper Reference ID:** pxc3879072

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