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Novel Distance Metric for Touch less Footprint Based Identification Technique

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Abstract: ***In this fast-paced technology-driven today's era, biometrics is not the new buzzword in the information security domain. Biometrics uses any physiological or/ and behavioral attribute/s of an individual for personal identification and/or verification. In biometrics, so many traits, like a fingerprint, face, palm, retina, iris, ECG, gait, voice, and signature, etc., have been used from ages to uniquely identify a human being. Biometrics based on Footprints is the latest practice for personal identification. Like fingerprints and palmprints, footprints of individuals carry uniqueness; hence can be used in biometrics for personal recognition. This work investigates the powerfulness of footprints by extracting texture and shape features using Principal Component Analysis (PCA) method based upon Eigenfeet and introduces a new distance metric during the matching phase. Experimental results show that the new distance metric shows better results in comparison to the Euclidean, Manhattan and Mahalanobis distances.***

Keywords: Biometrics, Footprint Recognition, Eigenfeet, PCA, Distance metrics

I. INTRODUCTION

Many popular modalities are being successfully implemented in biometrics like fingerprints, face, retina, iris, voice etc. But, the usage of footprint modality in biometrics, still, needs more stones to be unturned. Basically, Footprint Identification is the extraction and measurement of footprint features for recognizing the identity of a user [7]. Motivation behind using footprints has the following reasons:-

Firstly, like fingerprints and palmprints, footprints also carry uniqueness and remain persistent for a considerably longer period, so give more accurate results. Secondly, there are inexpensive and easy methods of acquiring footprint images. Thirdly, it is never possible to forge the footprints of a person. Footprint Recognition Systems have many real-time applications like forensic sciences against intruder identifications, or identity verification of newborns to protect them from baby switching [3], [11]. It also can be easily implemented in temples or holy places where only designated barefooted persons are allowed to enter near-sacred deity idol place, to save from malicious attacks [6]. Additionally, footprints could be used for those who are physically challenged e.g. persons having no hands. So instead of fingerprints, footprints could be used for legal purposes as an identification modality.

The organization of the paper is as follows: The next section presents an overview of background concepts, wherein, PCA method, Eigenfeet features and usage of both in the application for footprint recognition is discussed. Also, it discusses the various distance matrices, namely, Euclidean, Manhattan (or City Block) and Mahalanobis distances implemented for footprint recognition during matching phase. Section 3 describes the proposed approach which introduces a new distance metric. Experimental setup and test results are presented in section 4.This section also analyzes and compares the results to find the improved recognition rates. Finally, conclusion and future scope are discussed in the last section.

II. BACKGROUND

Since image acquisition and normalization of dorsal foot images is quite complicated, hence, observations are kept limited to planter foot images. Footprints can be acquired either through flatbed scanners or high resolution cameras [2]. Footprints can also be obtained using mat-type pressure sensors like FOOT ANALYZER [5]. Some Footprint Recognition Systems used pressure sensing mat like BIG-MAT to acquire and analyze the pressure distribution of footprints images [7]. Generally, Footprint Recognition Systems work in two modes: static (or standing) and dynamic (or walking) [1]. Current work is restricted to static mode only. Like other biometric systems, the proposed foot biometric authentication system consists of four steps namely, *image acquisition*, *preprocessing*, *feature extraction;* and *matching* and *decision* as shown in Fig. 1.They are described as below:

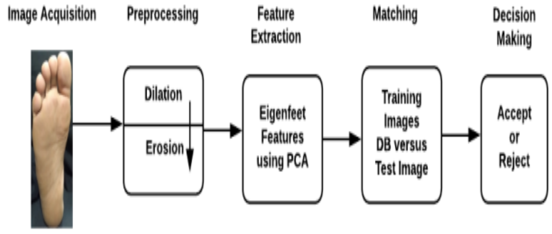

Fig. *1.* Schematic of Foot Biometric Recognition System

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A. Image Acquisition: Since there is no publically available online footprint database, the images are captured in real-time. Images of planter foot are captured using Canon EOS 1500 DSLR at 1080 dpi under the same environment and lightening conditions.

Preprocessing: Firstly, the acquired image is converted into the gray scale image G for further processing. Next , morphological *dilation* operation is performed using square structuring element S to close the boundary to get an image D:

$$D = G \oplus S = \bigcup_{s\in S}^{n} (G)_s \qquad (1)$$

Where, *Dilation* can be considered as a union operation of all the translations of image G caused by the elements specified in the structuring element S [4], [12]. Finally, morphological *erosion* operation is employed on the image D to get the transformed image I:

$$I = D \ominus S = \bigcap_{s\in S}^{n} (D)_s \qquad (2)$$

Where, *Erosion* is just the reverse of Dilation which uses intersection instead of union operation to get the common element [4], [12].

C. Feature Extraction: Feature extraction is the most crucial step in object recognition. Implementation of PCA (Principal Component Analysis) method using *Eigenfeet* on the processed footprint images is done to extract shape and texture features. Given below is the detailed description of PCA method and Eigenfeet generation.

1) **PCA:**

Introduction of PCA method dates back to Karl Pearson in 1901.It was used as a tool in exploratory data analysis and for making predictive models. It is the simplest method for the eigenvector-based multivariate analysis. It frequently is used to reveal the internal structure of data in a way which best depicts the major features / directions in the data e.g. variance. PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of M images say Foot images into a set of K uncorrelated variables called Eigenfeet. If a set of images (i.e. a multivariate dataset) is visualized as a set of coordinates in a high dimensional data space (one axis per variable), then PCA can supply the user with a lower dimensional picture; a “shadow” of this set when viewed from its most informative view point. Hence, it is mainly and the most popularly used method for dimensionality reduction in recognition and compression problems.

PCA method is also known as subspace projection technique which refers to the linear projection of image space to a low dimensional feature space called eigenspace. It seeks the projection of the data into the directions of highest variability. So, it tries to find the eigenvectors of the covariance matrix corresponding to the directions of the principal components of the original data. It transforms the original data image into a subspace set of principal components such that the first principal component of this subspace captures the greatest amount of variance among the images. The second principal component provides the basis vector of next directions orthogonal to the first principal component and so on. The last dimension of this subspace captures the least amount of variance among the images based on the statistical characteristics of the targets [2], [8], [10], [11].

In PCA, Eigenvectors generated are always orthogonal as covariance matrix is symmetric. Also, Eigenvectors constitute principal components which correspond to the direction (in original space) with the greatest variance of data. It generally discards principal components with zero or near-zero eigenvalues. Hence, it results in dimensionality reduction [2], [8], [10], [11].

2) **EIGENFEET:**

Usage of Eigenfeet feature in PCA method was motivated from Eigenfaces, introduced by Turk and Pentland [13] in 1991. The Eigenfeet are nothing but the most significant eigenvectors of covariance matrix. They are referred to as the projection of sub- sampled footprints onto feet space spanned by the most significant principal components. They contain the most relevant and common features of footprints. The Eigenfeet carry foot silhouette information in them hence, it can be called as a hybrid approach i.e. both shape based and texture based approach. Prerequisite of this method is that all the images must be *centered* and of the same *size*. Recognition task, involves following two major steps:

- ***Generation of Eigenfeet*** for training set of images and test image.
- ***Matching*** using a distance metric.

Generation of Eigenfeet involves the following sub steps:

1. Get *training set* of foot images $I_1, I_2 \ldots I_M$.
2. *Represent every m* x *n image I_i as a vector Γ_i* each of size *mn* x *1.*
3. Compute the *average foot vector* Ψ (Fig. 2):

$$\Psi = \frac{1}{M}\sum_{i=1}^{M} \Gamma i \qquad (3)$$

Fig. 2. Average Foot Vector

4. Subtract the average foot from every foot image vector Γ_i to get *normalized vector* ϕ_i:

$$\phi_i = \Gamma_i - \Psi \qquad (4)$$

The reason is to be left with only the distinguishing features from each foot and "removing" the common information.

5. *Find the covariance matrix C*:

$$C=\frac{1}{M}\sum_{i=1}^{M} \phi_i \phi_i^T = AA^T \quad (5)$$

where $A = [\phi_1, \phi_2, \phi_3, \ldots \phi_M]$

6. *Compute Eigenvectors with corresponding eigenvalues:* Since the matrix AA^T is very large (m^2 x m^2), so to compute the eigenvectors u_k in accordance with the eigenvalues λ_k and to have simpler calculations, matrix A^TA (m x m) is considered. Now, AA^T and A^TA have the same eigenvalues and their eigenvectors are related as: $u_k = Av_k$. Also, the L eigenvalues of A^TA correspond to the L *largest* eigenvalues of AA^T along with their corresponding eigenvectors. Hence, find L best eigenvectors u_i, corresponding to the K largest eigenvalues. These L highest eigenvectors are called *Eigenfeet*, which carry the most relevant foot features [2]. Since, they are the ghostly and weird images, hence, called so. Following Fig. 3 shows the images of computed Eigenfeet of 9 footprints.

Fig.3. Eigenfeet

7. *Feature Extraction:* It includes two sub steps-

7.1 *Computation of the basis vector:* It uses the normalized foot vector ϕ_i (Step iv) that is projected onto eigenspace to get the feature vector (or basis vector) components

$$\omega_i = u_i^T \phi_i \quad (6)$$

7.2 *Representation of each foot image as a linear combination of basis vectors:* Every Normalized foot image ϕ_i can be represented as a linear combination of basis vectors i.e. ϕ_i can be approximated by exactly L components:

$$\phi_i \sim \sum_{i=1}^{L} \omega_i u_i \quad (7)$$

(a) **(b)**

Fig. 4. a) Original Training image b) Reconstructed Training image

In the testing phase, the feature vectors of test foot image are extracted by following normalization and projection steps followed on test foot image (Fig. 4).

D. Matching:

Finally, matching phase comprises of calculating minimum distance technique by implementing four types of distance algorithms, namely Euclidean, Manhattan (or City Block), Mahalanobis and the proposed distance metric. Following are the definitions of the various distance metrics used:

a) **Euclidean Distance:** The Euclidean Distance is the most commonly used distance metric. It is a special case of a general class of norms and is given as:

$$dist_E((x, y), (a, b)) = \sqrt{(x-a)^2+(y-b)^2} \quad (8)$$

Where (x, y) and (a, b) are the coordinates of two points.

b) **Manhattan (or City Block) Distance:** It is the distance between two points measured along axes at right angles. It represents the sum of the absolute values of the differences of the coordinates.

$$dist_{CB}((x, y), (a, b)) = |x - a| + |y - b| \quad (9)$$

c) **Mahalanobis Distance:** The Mahalanobis distance is the distance between two points in multivariate space that takes into account the covariance between the variables. It is a measure between a point P and a distribution D, Hence, removes the problems related to scale and correlation inherent with Euclidean and Manhattan Distance. It is calculated as:

$$dist_{MH}((x, y), (a, b)) = \sqrt{(x-a)^T C^{-1} (y-b)} \quad (10)$$

Where C^{-1}= covariance inverse matrix. From the results of [15] PCA+MD outperforms significantly in comparison to PCA+ED in face recognition.

III. PROPOSED WORK

The proposed personal recognition system uses human footprints by implementing PCA and Eigenfeet approach and integrating a new distance metric. The diagrammatic representation of proposed work is shown in Fig 5. Following Algorithm is implemented in proposed footprint recognition system:

1. Input the preprocessed foot image I of size *m* x *n*.
2. Convert the image I to foot vector of size *mn* x *1*.
3. Normalize the foot vector using average foot image of training set.
4. Project normalized foot vector onto the eigen foot space.
5. Find the basis vector.
6. Perform matching by calculating the minimum distance between input basis vectors and all the weight vectors of training set using proposed distance metric.

7. Give the decision as accept or reject the claimed user.

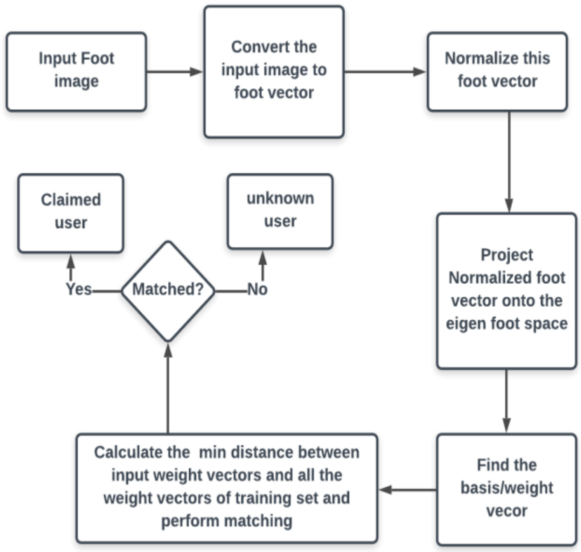

Fig. 5. Schematic description of Recognition steps of proposed work

Proposed Distance Metric: This distance metric is a variation of Mahalanobis distance which takes into account the covariance matrix instead of taking the inverse of covariance matrix. It is given as:

$$dist_{PD}((x, y), (a, b)) = \sqrt{(x - a)^T C\ (y - b)} \qquad (11)$$

Where **C**= covariance matrix of data points which needs to be positive definite matrix. This distance matrix gives faster and better performance. It has many reasons; in comparison to Euclidian and Manhattan, it considers the variances among the data points.

Also, it differs from Mahalanobis distance in the only way that it considers only the covariance matrix unlike inverse of covariance matrix which involves more computations.

So, recognition performance of proposed distance metric produces significantly better results when the image dataset is heavily populated and has larger image sizes.

Hence, when this new distance was implemented in matching phase, it gave better results in comparison to Euclidean, Manhattan and Mahalanobis distances.

IV. RESULTS AND DISCUSSIONS

To investigate the general applicability of the proposed approach and to achieve more recognition accuracy, the Footprint Recognition system was implemented using MATLAB.

The experiments were conducted by using our database of 60 footprint images of 45 females and 15 males of 12 people aged between 20 and 60.

Five footprint images of every person were recorded with the camera on the same day. Image acquisition is preceded by cleaning the sole of the user.

All the images are captured under the same environment i.e. same lightening conditions within a time span of 15 minutes per user.

The frontal pose was considered i.e. planter foot images centered in the image. All the images are cropped and resized to 1140 X 512 pixels.100 genuine attempts were executed means each footprint was matched against the remaining images of the same foot and 120 imposter attempts on the test set.

Four types of algorithms are tested, namely Euclidean, Manhattan, Mahalanobis and the proposed distance metric.

During matching phase, the best match of probe in the training set is the choice of subject r that minimizes the distance between probe image and each image in the training set. i.e.

$$\min_i \| C_r - C_p \|$$

Where, C_r and C_p are the vectors of coefficients in eigenspace for training and probe footprint images respectively [14].

So, the minimum distances between each test image and all the images in training image set were recorded. Similar processing steps were repeated every time for each type of distance classifiers.

For an instance, Table I shows the listing of respective min distances of 12 footprint test images using Euclidean, Manhattan, Mahalanobis and the proposed distance metric. Additionally, the total time elapsed for the recognition process was also recorded by implementing all the four distances.

Table II shows the elapsed time in seconds for foot recognition system using these distance metrics. A corresponding diagrammatic comparison of the elapsed time has been represented in Fig. 6 given below.

It is evident from table II and Fig.6 that the recognition process works faster using proposed distance metric as it takes lesser amount of time in comparison to Euclidean, Manhattan and Mahalanobis distances.

Table I: Minimum Distances of various Distance Metrics during matching phase

S. N.	Euclidean	Manhattan	Mahalanobis	Proposed
1	0.5844	2.01770	7.63E-05	7.66E+03
2	0.8661	2.57250	9.43E-05	9.18E+03
3	1.1995	2.50410	1.12E-04	1.08E+04
4	1.0735	2.49320	1.09E-04	9.86E+03
5	1.4043	2.52900	1.96E-04	7.15E+03
6	1.3896	2.58390	1.88E-04	7.41E+03
7	2.3453	1.10870	6.23E-04	3.76E+04
8	0.4619	1.54180	8.31E-05	5.56E+03
9	0.5348	1.76210	5.66E-05	9.45E+03
10	0.4237	1.67940	5.02E-05	8.45E+03
11	0.3802	1.58620	6.12E-05	6.22E+03
12	2.0106	3.16410	2.98E-05	3.03E+07

Table II: Time elapsed in seconds for recognition process in FRS using various distance metrics

S.N.	Time Elapsed in Seconds			
	Euclidean	Manhattan	Mahalanobis	Proposed
1	10.507496	10.977376	10.984230	10.089760
2	11.109633	10.979376	10.207997	9.829409
3	11.183020	10.239787	13.335142	9.462796
4	12.497053	12.370156	12.281769	10.662704
5	11.399549	11.417704	11.283798	10.995319
6	11.075330	10.609363	11.125690	10.316953
7	14.161996	11.608094	12.797149	10.523178
8	10.941541	11.343445	13.916569	10.431704
9	10.836558	13.524714	10.970531	10.724488
10	10.968256	11.330472	12.182584	10.136835
11	12.105550	12.663311	11.170535	10.224616
12	14.981370	13.669041	13.998666	10.483433

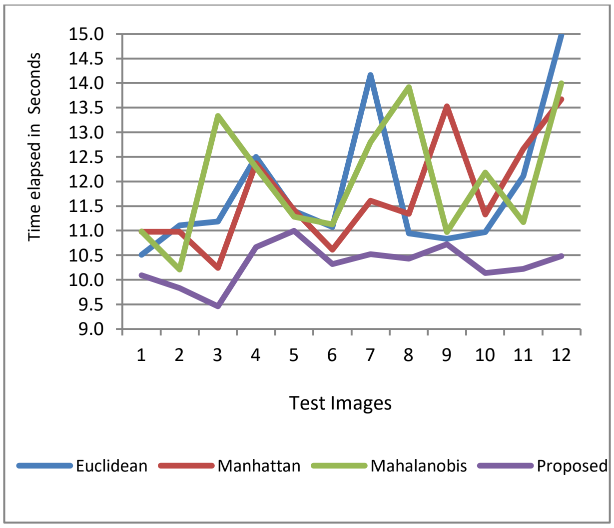

Fig.6. Comparison of time elapsed for recognition by using Euclidean, Manhattan, Mahalanobis and Proposed distance metric distance metrics

On the basis of the results illustrated in table II and in Fig. 6, it can be seen that implementation of proposed distance metric produces faster recognition in comparison to other three distances. Hence, the proposed approach is faster yet more efficient for Footprint Recognition System using PCA and Eigenfeet approach.

Afterwards, the recognition rates for all the four distance classifiers were calculated. The most popular performance measures used in biometrics are FRR (False Reject Rate), FAR (False Accept Rate) and Accuracy. So, the results are tested for FAR, FRR and Accuracy of the recognition system. FRR (or, False Non Match Rate (FNMR)) refers to the rate at which the system incorrectly rejects access to an authorized person. On the other hand, the rate at which the system falsely authorizes a non-authorized person is termed as FAR (or, the False Match Rate (FMR)) [11]. Finally, the Accuracy governs the efficiency of the system in terms of its ability to identify a person which is dependent on the values of FRR and FAR both. The FRR, FAR and Accuracy are expressed in terms of percentages as below:

$$FAR=\frac{(No.of\ false\ acceptance\ found)}{(Total\ no.of\ comparisons)}\ x\ 100 \quad (12)$$

$$FRR=\frac{(No.of\ false\ rejections\ found)}{(Total\ no.of\ comparisons)}\ x\ 100 \quad (13)$$

$$Accuracy=100-\frac{(FAR+FRR)}{2} \quad (14)$$

Table III: *FAR, FRR and Accuracy of various distances*

Distance classifier	FAR(%)	FRR(%)	Accuracy (%)
Euclidean	4.22	6	94.82
Manhattan	5.85	4	95.07
Mahalanobis	3.42	6.45	95.65
Proposed	**2.62**	**3**	**97.19**

Table III shows verification rates (in terms of FRR and FAR) and accuracy of various distance metrics employed in the proposed system. Fig. 7 and 8 show the comparison of error rates (FAR and FRR) and accuracy of the system implementing all the four distances including proposed distance metric.

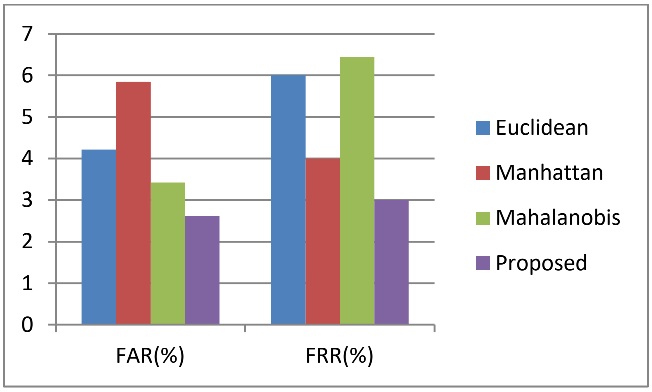

Fig.7. Comparison of FAR, FRR

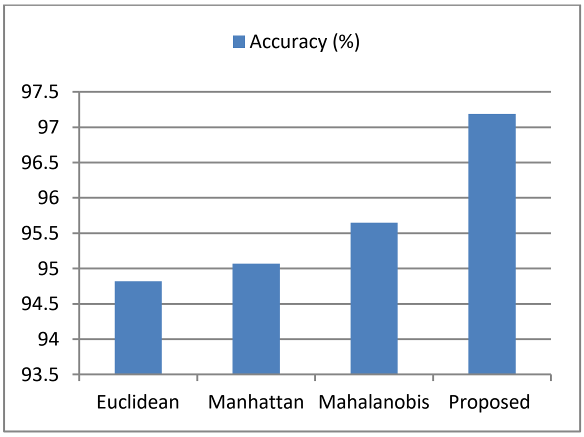

Fig.8. Comparing Accuracy among four distance metrics

From the results of Table III and Fig. 7 and 8, it is evident that proposed distance metric shows better recognition performance compared to other distance metrics due to lesser error rates and higher accuracy. Hence, it proves to be more effective and better recognition system.

V. CONCLUSION AND FUTURE WORK

In this paper PCA Algorithm is employed based on Eigenfeet for footprint Recognition. In biometrics, most of the recognition algorithms have used either the Euclidean distance or Manhattan (or city block) distance during the matching phase. In this paper, a new distance metric, which is a variation of Mahalanobis distance metric, has been implemented for footprint recognition for the first time. Results show that it matches in a more improved and faster way. In the Mahalanobis distance, different components of feature vector play different roles when measuring the similarity between features. The new distance metric and the Mahalanobis distance metric, take into account the covariance among the data set. Experimental results demonstrate that proposed distance metric can significantly outperform Euclidean, Manhattan, and Mahalanobis distance metrics during footprint recognition using PCA and Eigenfeet, making it a new and first effort in the direction of biometrics especially for footprint recognition. This footprint recognition can further extend its applicability in various areas like New born baby Authentication, Forensics, Multimodal Biometric Authentications, Medical Diagnosis for finding the foot deformities, etc.

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