for each database, 3080 genuine matchers are executed and 348,800 imposter matches are executed. The matching score in the first level is computed based on the Euclidean distance between two DVFs constructed as described in section 3.3. None of the genuine matching score is zero as images from the same finger had not generated identical DVFs because of distortions and rotation.

The decision is based on a boundary (i.e. threshold) that minimizes FAR and FRR. FAR and FRR values for different decision thresholds as a result of matches performed in this work after the initial matching step using global characteristics are shown in Table 1. When FAR is 2.3%, FRR is 2.25% and Equal Error Rate (EER) is 1.82%. The efficiency of the proposed fingerprint matching based on DVFs has been compared with the Fingercode matching scheme as proposed in [2], and Figure 8 shows the Receiver Operating Characteristic (ROC) curves for the two matchers evaluated on FVC2002 databases.

Table 1: False Acceptance and False Rejection Rates with different threshold values for the FVC2002 DB1 and DB2 databases

Threshold value	FAR (%)	FRR (%)
0.1	0.05	19.2
0.2	0.3	4.53
0.3	1.23	2.41
0.4	2.3	2.25
0.5	3.95	1.8
0.6	23	0.1

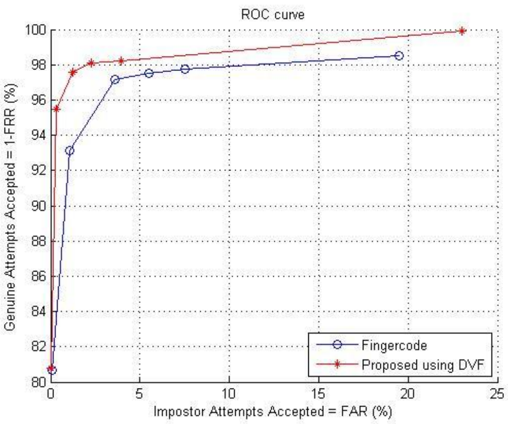

Figure 8. ROC curves of the proposed matching using DVFs and Fingercode [2]

The basis for choosing to compare the proposed method with [2] is that it has been the most popular technique to match fingerprints based on texture information during the past decade. In [2], if the Euclidean distance between two Fingercodes is less than a threshold, a decision is made that the two images come from the same finger, otherwise a decision that the two images come from different fingers is made. Determining the threshold is a tradeoff between the two types of errors (FAR and FRR). If a higher threshold is chosen, the genuine acceptance rate is lower, but FAR may be higher and vice versa [2].

In this proposed technique, at the first level matching, two thresholds t_1 and t_2 are chosen to determine match and non-match respectively. A decision is made that the two images come from the same finger if the match score ms_{DVF} based on the Euclidean distance of the DVFs of I and S is less than t_1 and from different fingers if greater than t_2. Threshold t_1 is chosen with minimum FAR and threshold t2 is chosen with sudden rise in the imposter matches. The values of t1 and t2 chosen are 0.1 and 0.6 respectively in this work. There is an uncertainty in the fingerprint images whose matching scores lies between t_1 and t_2 as to whether they are from the same finger or not. This is due to the fact that the stored fingerprint representation may not be invariant to large perturbations or both the input and stored templates may be from different fingers but belonging to the same class exhibiting similar pattern around the reference point as the DVFs used for matching captures more of the global pattern. It has been observed that genuine matches are high and imposter matches are low even for low-quality images and hence robust to noise.

Samples of possible fingerprints whose similarity scores (ms_{DVF}) lying between t_1 and t_2 are shown in Figure 9 and these progresses to the second level for accurate matching process. Experimental analysis on FVC2002 database for the proposed hierarchical strategy shows that, on the average 78.8 % of the fingerprints get filtered after the first level matching with either a match or non-match decision. Moreover, the feature vector (DVFs) is very compact and requires only 16 bytes irrespective of the image size.

The finer second level matching is performed based on the local structures LSs extracted from S and I as discussed in section 5. The small spatial distance threshold value Δt (1.5 in this work) is chosen after analyzing the LSs generated for various fingerprint images.

Figure 9 (a) Finger impressions belonging to the same finger (b) impressions of different fingers belonging to the same class exhibiting similar patterns around the reference point.

It has been observed that the combined matching score *(CMS(I,S))* computed using Equation 8 based on global attributes and local structures is

a) Between 1 and 2 for fingerprint images belonging to the same class but different finger.

b) Less than 1 for images belonging to different class and finger.

c) Between 2 and 3.5 for fingerprint images belonging to the same finger but with different orientations with large perturbations.

d) Greater than 4 for same fingerprint with similar orientation.

Based on these observations the match/non-match threshold (T=3) has been chosen. If the similarity score is greater than T, then the decision that "*the two images belong to the same finger* is made, or else a decision that *the two images originate from different fingers" is made*.

Table 2 presents the EER results as recorded in the respective papers for FVC2002 databases along with the proposed matching scheme and their corresponding ROC curves is shown in Figure 10. The processing time of the proposed system is given in Table 3.

Table 2: Matching performance (EER%) of existing algorithms with proposed method

Algorithm	Feature/Structure Topology	EER(%)
Filterbank[2]	Fingercode	4.87
K-plet[28]	Minutiae-graph	1.5
Xiang[9]	Minutiae Tensor matrix(MTM)	0.8
Rodrigues [11]	Minutiae-Planar Graphics	1.14
Proposed(Stage 1)	DVF	1.6
Proposed(Stage 2)	DVF +LS(minutiae)	0.65

Table 3: Processing time of the proposed method

DVF		LS	
Feature Extraction	Matching (1:1)	Feature Extraction	Matching (1:1)
0.0354	0.0035	0.9381	0.0443

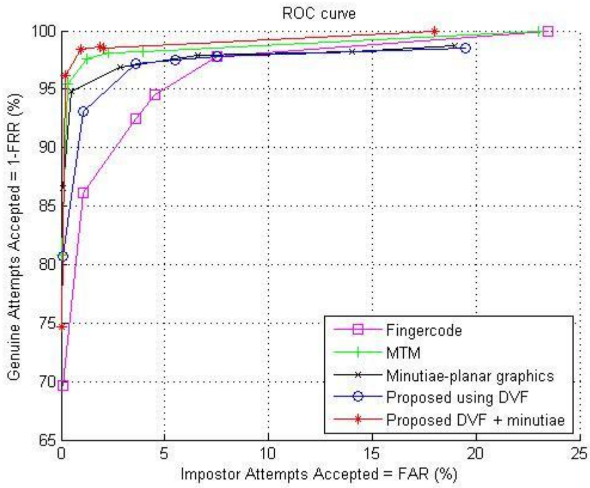

Figure 10. Comparison of the proposed method along with existing methods using ROC curves for FVC2002 database

CONCLUSION

The proposed hierarchical matching algorithms have used features based on global characteristics (DVF) that exhibit high distinctiveness among different classes and local structure matching (LS) that can tolerate high rotation distortions. Experimental results show that the overall accuracy of the proposed matching system by combining results of independent matchers based on DVF and LS fingerprint representations has significantly improved (EER 0.654%). The developed matching system can be deployed to control physical device access by integrating fingerprint recognition into laptops, tablets, smart phones and other electronic devices that have personal and sensitive data.

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