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Fusion of finger types for fingerprint indexing using minutiae quadruplets

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ABSTRACT

Accuracy, security and efficiency are the drivers for exploiting multibiometric systems. A multi-modal or multibiometric system is relatively more secure than a single-biometric system as a result of the rich biometric content, lower error rates and resilience to impostor attacks. The availability and easy acquisition of the ten prints of an individual with fewer resources, give multi-finger biometric fusion scheme an advantage over other fusion schemes based on different biometric modalities. In this paper, multi-finger indexing is proposed using minutiae quadruplets in combination with a clustering scheme. Four, five and ten fingerprints from a subject are fused at the rank level using the highest rank rule. The minutiae quadruplet features are observed to be robust and the clustering scheme assists in quickly identifying a list of potential candidates in the gallery database. Results from the experiments show good performance of the fusion scheme with minutiae quadruplet features in fingerprint indexing.

1. Introduction

1.1. Biometric fusion

Multiple sources of information are combined in a multibiometric system to improve matching performance (Jain et al., 1999; Maltoni et al., 2009; Rodriguez et al., 2008; Ross and Jain, 2004; Ross et al., 2006; Vatsa et al., 2010). Rather than using a single biometric sample of a subject, information from multiple samples of the same biometric of a subject (e.g., different facial poses) or different biometric traits of a subject (e.g., face and fingerprint) could be combined to enhance the performance of a biometric system.

The use of multiple sources of information has several advantages over single-biometric systems. The amount of information in a single biometric is limited whereas the availability of multiple biometrics results in richer biometric content (Ross and Jain, 2003). Multimodal biometric systems can be judiciously used to resist impostor attacks. The error rates associated with these systems can also be minimized. It is unlikely that a false reject or false accept corresponding to one biometric of a subject would also occur with the other biometric traits of the same subject. Accuracy, security and efficiency are the drivers for exploiting multibiometric systems. In multimodal systems (which utilize different biometric traits), the combination of traits could improve or undermine performance depending on the traits being used and the mechanism adopted for fusion. It is essential, therefore, to know what biometrics should be combined and at what level they should be combined.

Fusion refers to the point of integration of multiple sources of information in a multibiometric system. Fusion of biometric traits is currently done at these levels: signal, feature, score, rank and decision levels (Maltoni et al., 2009; Ross et al., 2006). Rank level fusion is used in this paper.

The fusion of biometric signals acquired from a sensor or multiple sensors is called signal level fusion. A biometric signal can be acquired from a sensor in the form of voice, video (3D face, gait sequence), motion (dynamic signature) or image. Signals fused at this level need to be compatible; therefore this fusion scheme is normally employed for combination of multiple signals of the same biometric trait of an individual.

Feature level fusion is the combination of multiple feature sets extracted from the biometric samples of an individual. Fusion at the feature level is demonstrated in Choi et al. (2011), Hariprasath and Prabakar (2012), Nagar et al. (2012), Rattani et al. (2006), Roli et al. (2002), Ross and Govindarajan (2005), Chetty and Wagner (2005), Yang and Zhang (2010).

Score level fusion is the combination of match scores resulting from use of several classifiers in a multibiometric system. Score level fusion is a widely researched and adopted approach because of its ease of implementation compared to signal and feature levels fusion (Dass et al., 2005). In Gyaourova and Ross (2009, 2012), He et al. (2010), Kumar and Zhou (2012), Marcialis and Roli (2007), Merati et al. (2012), Poh et al. (2009), Ren et al. (2009), Sha et al. (2007), Chetty and Wagner (2008), Vatsa et al. (2007), Yang and Ma (2007), Prabhakar and Jain (2002), Paulino et al.

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(2010), fusion is carried out at the score level to fuse different algorithms or multiple instances of similar or different traits.

Decision level fusion is the consolidation of the individual decisions taken by several classifiers. Decision level fusion is also known as fusion at abstract level (Ross et al., 2006). This approach uses less detail and has a number of dependencies on the prior stages (Maltoni et al., 2009; Yang et al., 2011). Fusion has been carried out at the decision level in Yang et al. (2011), Mueller and Martini (2006).

In an identification system, match scores between a probe and all database (i.e., gallery) identities are ranked in descending order of similarity. The highest score (the first score) on the sorted list would correspond to Rank 1 and would be assumed to be the score of the enrolled identity that is most similar to the query print or probe under consideration. Rank level fusion is the combination of the ranks output by each classifier's one-to-many comparisons in a multibiometric identification system. The ranks from the classifiers would need to be fused based on any of these existing methods or rules such as highest rank, Borda count or Logistic regression (Ross et al., 2006). In the highest rank method, the final rank for each identity is computed by determining the highest rank from the weighted output ranks of the individual classifiers (Ross et al., 2006). Rank level fusion using the highest rank method is employed in this paper. Rank level fusion is easier to use than the first three levels already discussed and is suitable in an identification system (Abaza and Ross, 2009; Tahmasebi et al., 2011; Yin et al., 2010).

1.2. Fingerprint indexing

Fingerprint indexing is used in large-scale biometric databases like Automated Fingerprint Identification System (AFIS) where the size of the database can be in the millions. In fingerprint identification, an input fingerprint called a query print or probe is typically compared against a database of enrolled fingerprints called the gallery to seek a match. However, the task of comparing a query fingerprint against a large gallery is computationally challenging, intensive and expensive due to the large number of comparisons to be undertaken. This can substantially increase the response time of a large-scale fingerprint identification system. The time taken to find matching impressions to a set of probes in ten-print identification system (such as IAFIS – Intergrated AFIS) is indeed significant due to the multiple comparisons involved; hence the problem is more complex in an IAFIS compared to an AFIS.

Fingerprint indexing techniques are employed to reduce the search time for finding a matching identity to a probe. Indexing works by associating a probe with feature vectors or index codes that best describe their features (Cappelli et al., 1999). Fingerprint indexing techniques aim to select a few fingerprints in the database, called the candidate list, and the query print is compared with only the fingerprints in the candidate list by a matching algorithm. The candidate list should ideally contain the genuine print. In a 10-print identification system, the search time for a match would be reduced by limiting all probes searches to multiple candidate lists of fingerprints that include the genuine prints to the probes or one candidate list if a fusion scheme is adopted. The size of a candidate list should be significantly less than the gallery size if the indexing technique and scheme are efficient. Indexing techniques for reducing the search space in a gallery based on match scores, ridge features, texture-based or geometric features already exist in the literature (Cappelli et al., 2011a,b; Choi et al., 2011; He et al., 2009; Iloanusi et al., 2011; Ross and Mukherjee, 2007; Wang and Hu, 2007).

Penetration rate and hit rate are the two key performance factors considered for efficient indexing. The performance of an indexing scheme is determined by the penetration rates and hit rates of all the probes used in the evaluation. The penetration rate is the fraction of user identities retrieved from the gallery upon presentation of a probe, and the hit rate is the probability that the genuine print is retrieved (Ross and Mukherjee, 2007). Lower penetration rates result in a better fingerprint indexing algorithm; hence, the goal is to have lower penetration rates at a hit rate of 100%. If a candidate list contains the genuine matching identity to a probe, a hit is said to have occurred. The hit rate considered in the section on Experiments is a function of the number of all the probes used in the evaluation.

This paper proposes using geometric features termed minutiae quadruplets in combination with the clustering retrieval strategy for indexing fused fingerprints. Minutiae quadruplets have already been proposed in Iloanusi et al. (2011) but is extended to fused fingerprints in this paper. Fingerprints are fused at the rank-level employing the highest rank rule in three scenarios: fusion of four fingers, five fingers and all ten fingers.

The rest of the paper is organized as follows: Section 1 introduces biometric fusion and fingerprint indexing. Section 2 discusses the features for indexing and the indexing retrieval strategy, while the fusion scheme is discussed in Section 3. Section 4 presents and discusses the experiments; then, the proposed scheme is compared with other fusion schemes in Section 5.

2. Indexing features and technique

2.1. Minutiae quadruplet features

A fingerprint comprises several or many minutiae quadruplets depending on the number of available minutiae points in a fingerprint. A feature vector, F, is derived from the geometrical measurements in a quadruplet. The minutiae quadruplet structure has seven features:

$$F = \{\varphi_1, \varphi_2, \delta_1, \delta_2, \rho_1, \rho_2, \eta\} \tag{1}$$

The geometrical interpretations of δ_1, δ_2, ρ_1, and ρ_2 and components of φ_1, φ_2 and η from a given minutiae are shown in Fig. 1 (Iloanusi et al., 2011). φ_1 and φ_2 are the differences of two opposite interior angles in a quadruplet.

$$\varphi_1 = \theta_1 - \theta_3 \tag{2}$$

$$\varphi_2 = \theta_2 - \theta_4 \tag{3}$$

δ_1 and δ_2 are the two diagonals of a quadruplet. ρ_1 and ρ_2 are the two perpendicular heights of the quadruplet's inner parallelogram.

The last feature η is integrated from both polygons – the quadruplet and parallelogram. This feature is unique to every quadruplet because it is characteristic of each quadruplet's shape and size.

The global feature, η, is derived as follows:

$$\eta = 100\log_{10}(\tau v) \tag{4}$$

where

$$\tau = \sqrt{A_p} + \sqrt[4]{x_1 \times x_2 \times x_3 \times x_4} \tag{5}$$

$$v = \sqrt{A_Q} + \sqrt{y_1 \times y_2} \tag{6}$$

where A_p is the area of the inner parallelogram of sides, y_1 and y_2, and A_Q is the area of the quadruplet of sides, x_1, x_2, x_3 and x_4.

A fingerprint may be characterized or indexed with a set of minutiae quadruplets. It is expected that the values in a minutiae quadruplet will be similar between corresponding minutiae quadruplets from different impressions of the same fingerprint and differ amongst quadruplets of different fingerprints. The quadruplets of the gallery images are extracted offline.