Study of the Distinctiveness of Level 2 and Level 3 Features in Fragmentary Fingerprint Comparison

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Abstract. In this paper we present the results of an experiment which aims to provide an insight into the problems related to the fingerprint recognition from its fragment. Level 2 and Level 3 features are considered, and their distinctive potential is estimated in respect to the considered area of a fingerprint fragment. We conclude that the use of level 3 features can offer at least a comparable recognition potential from a small area fingerprint fragment, as the level 2 features offer for fragments of larger area.

1 Introduction

The studies of distinctive fingerprint features have a long tradition. As early as 1872 a probabilistic analysis of selected level two features was performed by F. Galton [4].

Level one and level two features are related to the characteristic configuration of the ridges on the surface of the fingerprint. The characteristic ridge alignment in the center of the fingerprint is regarded as level one feature. The local discontinuities and links between ridges are considered level two features, otherwise referred to as the minutiae. The most prominent and common among the minutiae are the ridge terminations and bifurcations [7]. Level two features, are currently by far the most common feature set used for automated fingerprint recognition [4].

Level three features consist of local intra-ridge details, including the traces of the sweat pores distributed over the ridges. The pores are the termination loci of the sweat ducts that originate in the sweat glands in the dermis. An early description of the pores and their characteristics can be found in [2]. The position of the pores on the ridges is thought to be individual and distinctive for a given finger.

Level three features (the pores in particular) have only recently attracted the attention of researchers working in the area of automated fingerprint verification [10]. The reason for that can be sought in the fact that the pores are much finer features of the fingerprint than the ridges are, and they consequently require higher image resolution to detect. Due to the very same reason they are also more prone to the distortions of the image.

The main issue in biometric authentication based on any modality is the reliability of the comparison between the test and reference data, on the basis of the extracted features. The use of an additional feature level aims to provide additional distinctive information when verifying the identity associated with the fingerprint.

The performance of systems based on level 2 features is fairly well studied and documented [5]. Although it is possible to classify different methods of fingerprint recognition based on their performance [3], the question how distinctive and characteristic certain features of a fingerprint are, still remains relatively unanswered [8]. Even less is known of how much gain (if any) one can achieve by introducing an additional feature level.

Roddy and Stosz [7] attempted to do an extensive analysis of what verification performance can be expected from the employment of level 3 features. In their work they present a model of pore distribution which has very sound foundations in physiology. In particular, one of the underlying assumptions of their model is that the distribution of the pores follows a regular pattern, up to a specific randomness, and that is only modified by the ridge pattern (pores appearing only on the ridges, not in the valleys). The weak point of this model is that naturally a fingerprint is distributed over a 3D surface, while scanning with different methods forces the fingerprint to be a planar projection of this surface. This introduces deformations which make the assumptions about the regularity of the pore spacing rather not realistic.

It is a hard task to model the nature of the mechanical deformations of a 3D-fingerprint surface [9]. One can easily imagine a distortion large enough to make a correction of such deformations unreliable, if not impossible. Also other factors (skin conditions, inherent fingerprint features, improper fingerprint positioning on the scanner) can render parts of the fingerprint useless from the viewpoint of an automatic verification system. In such a situation, the use of the least distorted fingerprint fragment (or multiple fragments) appears as a reasonable strategy.

In order to be able to predict the reliability of a verification procedure based on a fragmentary fingerprint input it is essential to know how the robustness of the matching method changes with the size of the fingerprint used. Equipped with such knowledge, one can consciously discard the distorted parts of the input fingerprint aiming for more reliable identity verification.

In the forensic sciences comparing fragments of fingerprints is a typical task. After an extensive analysis of a fingerprint fragment it is possible to decide about the identity based on the ridge shape, even if no level 2 features are present [6] – a scenario, where a minutiae-based automated system would fail. We hypothesize that for a partially distorted fingerprint, its undistorted fragment carries at least the same amount of distinctive information as its entirety. We also expect that the use of level 3 features may boost up the recognition accuracy particularly in the case of the comparison of fragmentary fingerprints.

To verify our hypotheses we conducted a pilot study, described in [1], and two experiments, described in the following sections of this paper. First, we provide an outline of the experimental design in Section 2. Section 3 contains details on experimental procedures, results of the experiments and their discussion. Section 4 presents final conclusions and prospects for future work.

2 Verification of Fingerprints from a Fragment

In order to estimate the reliability of verification of a fingerprint from its fragment we designed two experiments based on one-to-one match. This reliability depends on how distinctive are the features used in the comparison between the test and reference fingerprint. We want to investigate how the size of the available fingerprint sample affects the distinctive potential of the features extracted from the ridge structure, the minutiae and the pores.

Figure 1: Fingerprint and its fragment with visible minutiae and pores.

Typically, for any set of features extracted from the test and reference fingerprint a measure of feature match (score) is being computed. Then, a threshold is usually being applied to decide if the test fingerprint matches the reference. The choice of the threshold depends on the desired properties of the biometric system. The threshold T can be described as a function f, such that:

$$T=f(\mu_A,\sigma_A,\mu_D,\sigma_D). \quad (1)$$

The function f takes as arguments (μ_A,σ_A) which are the mean and corresponding standard deviation of the distribution of a match score between fingerprints (or their fragments) originating from the same finger. We therefore refer to this score as the *accord score.*

Similarly, the arguments (μ_D,σ_D) describe the recognition system's response to a match between fingerprints (or their fragments) that do not originate from the same finger. We refer to this score as the *discord score.*

The estimation of the appropriate thresholding strategy is out of the scope of this paper. Hence we restrain from trying to estimate the function f. Instead, we focus on the accord and discord score measurements. From those values, having secured that the scoring mechanism is constant over the entire experiment, we intend to draw conclusions about the distinctive content that the used features carry.

3 The scoring procedure and the database

The scoring algorithm was designed as follows: before comparison, the ridge, minutiae and pore features are extracted from the reference image. Namely, the ridge skeleton, and the coordinates of the minutiae and the coordinates of the pores are considered. The same features are also extracted from every test fingerprint fragment used in the experiment. The match score of the ridge structure is computed using normalized correlation, while the minutiae and pore features were compared based on a geometric distance criterion [4]. The details of data extraction and matching algorithms can be found in [1]. Resulting scores are from (0,1) range, where a '0' corresponds to a complete mismatch, and a '1' indicates a perfect match of extracted features.

In our experiments we used the database obtained from the IPS, UNIL[1]. The database consists of images acquired using a custom built optical scanner at the resolution of 1972×2849 pixels (ca. 2000 dpi). There are images of 6 fingers in the database, for each finger there are 10 separate fingerprints in the database. All fingerprints in the database are of comparable, high quality and were taken in same controlled conditions.

From the database we took sets of 4 fingerprints of the same finger. In total, we took such fingerprint sets of 6 different fingers. We indexed each fingerprint as X_Y, where X is the number assigned to a particular finger, and Y is the number assigned to one of the four images of X.

3.1 Accord scores

An accord score for a given feature set (ridges, minutiae or pores) was calculated for fingerprint fragments that are known to originate from the same finger.

Fingerprint sets 1-6_1 and 1-6_2 were considered reference sets, while 1-6_3 and 1-6_4 were used as source of test images. Two separate experiments were performed: in the first experiment images from the test set 1-6_3 were compared to the reference set 1-6_1 (further called image set X_1), while in the second experiment the fingerprints from the test set 1-6_4 were compared with the reference set 1-6_2 (further called image set X_2).

For each pair of images under comparison, the reference image remained intact, while the test image was systematically fragmented and the resulting fragments compared to the reference image. In each subsequent fragmentation step the dimensions of the resulting sub-images (fragments) of the test image were:

$$[x_n,y_n]=[x_0,y_0]\cdot K^n, \qquad (2)$$

where $[x_0,y_0]$ are the dimensions of the original reference image, $[x_n,y_n]$ are the dimensions of the test fingerprint image at the n^{th} fragmentation step, and K is the factor that controls the reduction of the fragment size between subsequent fragmentation steps. In our experiment we choose K=0.75 in order to arrive at a small test

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fragment size in reasonably few fragmentation steps. We call the value of *n* the *fragment size index*. An example of the original test image and its sub-images at subsequent fragmentation steps is shown in Figure 2.

Figure 2: Subsequent fingerprint fragmentation steps according to equation (2). From left to right: original image from the database, with automatically removed background, subsequent sub-images of fragment size index *n*=1,2,3,4,5.

Before scoring, the test fragment was automatically aligned with the corresponding fragment of the reference image. We used normalized correlation for the alignment procedure. We have presented the details on the choice of features used in the alignment procedure and the procedure itself in [1]. Both the tested image and the corresponding, automatically located reference fragment had to have more than 90% of their area occupied by the ridge structure (less than 10% background) in order to be scored. Every comparison returned the ridge, minutiae and pores accord score. If the algorithm failed to align the test fragment with the reference image the reported ridge matching score was set to null.

3.2 Experimental results – accord scores

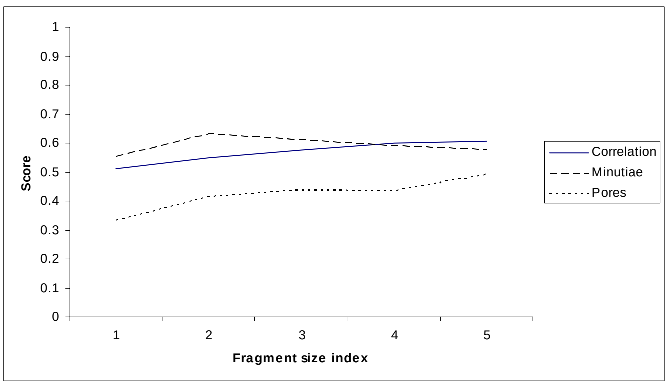

Figure 3: Average accord scores for comparison with the reference set X_1.

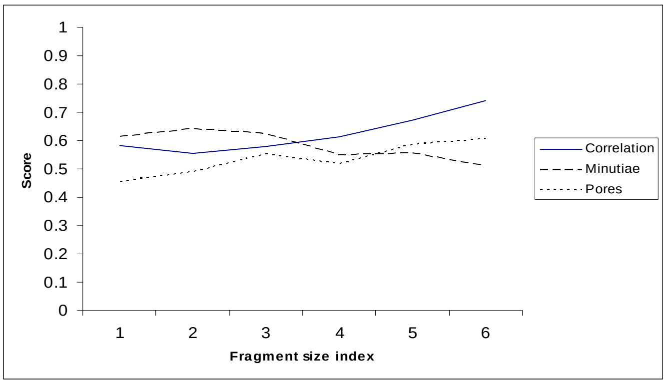

Figure 4: Average accord scores for comparison with the reference set X_2.

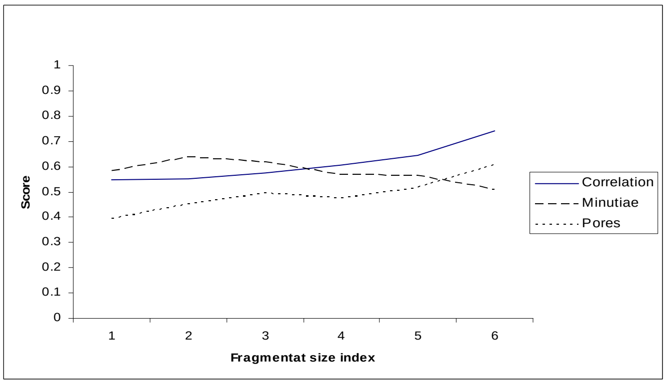

Figure 5: Combined average accord scores for reference sets X_1 and X_2.

The accord scores show some consistent tendencies. With the decreasing size of the test fingerprint fragment the correlation scores between the test and reference fingerprint increase. This result at the first glimpse could be thought counterintuitive. It nevertheless agrees with our initial presumption that reducing the test fragment size will reduce the misalignment due to local mechanical distortions present in the 2D projection of the finger surface. It also indicates that localizing smaller fragments of a fingerprint on the area of the reference fingerprint is likely to be more reliable than alignment of a larger fragment (or the entire fingerprint).

This conclusion holds only if we assume that the aligned fragment has been located correctly. One could suspect that with reduced area to be matched the likelihood of finding an area that is similar enough to produce high correlation value will grow. This cannot be dismissed based on the analysis of the correlation scores alone.

The minutiae-based match accord scores drop as we reduce the size of the test fingerprint fragment. This could be due to a hypothetical misalignment of the test fragment with the reference image. However, the observed drop is not large enough to be due to a misalignment, particularly, that as we go down with the fragment size the chances of finding similar minutiae configuration by sheer luck vanish. There is an-other plausible explanation for the diminishing minutiae match scores. Reducing area of a fingerprint fragment also decreases the number of minutiae present in this fragment (Figure 6), thus even a small mismatch between the test and the reference minutiae distribution lies heavily on the score.

The pore matching accord score displays an upward tendency as we reduce the test fragment of the fingerprint. The vast number of detected pores in a large fingerprint area makes the comparison difficult and unreliable. Even small ridge misalignments due to distortions produce large displacements of pores, relative to their sizes. For small fingerprint fragment the number of pores shrinks considerably (Figure 6), but remains large enough to make a meaningful match. The growing pore matching accord score also gives support to the presumption that the correlation-based alignment is correct. Should it be not – there would be no reason for the pore match accord scores to grow – they should in this case stay at best constant.

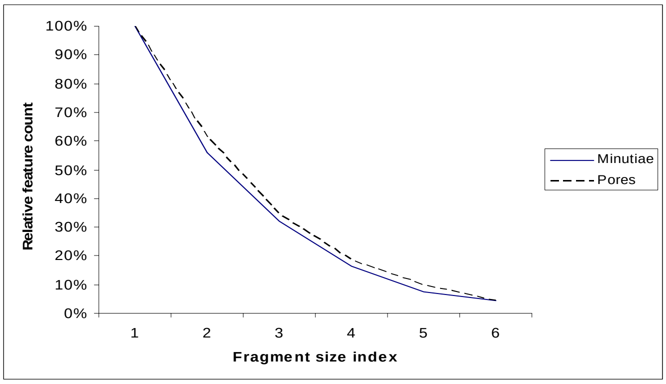

Figure 6: Relative reduction in the minutiae and pore count as a function of reduced fingerprint fragment size.

Figure 6 shows relative changes in the amount of the minutiae and pores found in a fingerprint fragment of diminishing size, averaged over all fingerprints used in the reported work. A 100% score corresponds to the feature count for the fragment size index n = 1, where the average number of minutiae and pores was 73.8 and 425.5, respectively (accord scores, reference set X_1), and 69.3 and 511.75 (accord scores, reference set X_2).

3.3 Discord scores

A discord score for a given feature set (ridges, minutiae or pores) is calculated for fingerprint fragments that are known not to originate from the same finger.

Six pairs of images originating from different fingers were assembled. Following pairs of fingerprints were compared (Table 1):

Table 1: Image pairs used in the discord score calculations.

Reference set	1_1	2_1	3_1	4_1	5_1	6_1
Test set	3_2	4_2	5_2	6_2	1_2	2_2

The comparison and matching procedure was similar as in the case of the accord scores. However, since by definition the test and reference fingerprints do not match, the algorithm was not attempting to align the test fragment with the reference image. Instead, the test fragment was scored against a randomly chosen fragment of reference fingerprint of the same size.

3.4 Experimental results – discord scores

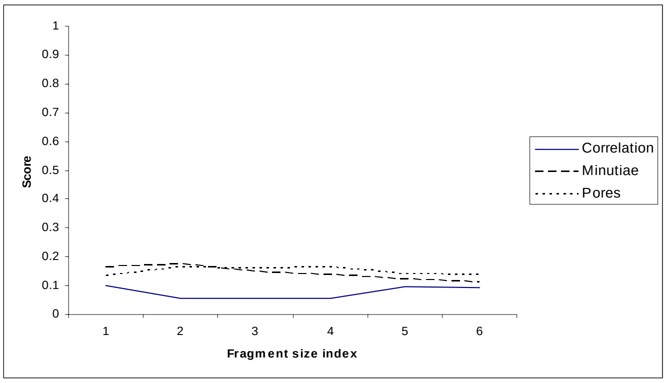

Figure 7: Average discord scores for diminishing fragment size index.

The results of the discord score measurements show the average comparison scores between non-matching fingerprint fragments of various sizes. As Figure 7 shows, the discord scores for ridge- minutiae- and pore-based comparison remain fairly constant, regardless of the size of the test fingerprint fragment. They also remain clearly separated from the accord scores (Figures 3, 4 and 5). This interesting result allows us to conclude that the considered fingerprint features are distinctive enough to be robust in the case of even small fingerprint fragments.

The constant discord scores for pore-based match provides support for the argument on the correctness of correlation-based match presented in section 3.2. If the raising correlation accord score would be associated with misalignments of the test image with the reference image, for all those cases the calculated pore-based scores would in fact be discord scores. As the experimental data presented in Figure 7 show, in such case the pore-based scores should remain at best constant, instead of having a growing tendency.

The discord scores measure the average similarity between two randomly chosen fingerprint fragments of identical size, where we are certain that they do not originate from the same fingerprint. In a real-life automatic fingerprint verification system such notion cannot exist, and the system is bound to attempt the best alignment of the test fragment with the reference image, regardless of their origin. We have addressed this scenario in [1].

4 Conclusions and future work

Based on the results of the presented work, we analyzed the relations between the distinctive information contained in the ridge structure, and the selected level 2 and level 3 features. The results indicate that using a fragment instead of the entire fingerprint can produce at least equally reliable recognition result, given sufficiently high fingerprint quality (level 3 features must be detectable). From our current results alone it is not possible to state that the recognition results would be better when using a fragment instead of the whole fingerprint, particularly if the entire test fingerprint is of high quality (like in the case of the database used in our experiments). It can be however speculated that if the fingerprint would be heavily locally corrupted, verification based on only undistorted fragments would produce more reliable results than a holistic approach. Also, for fingerprints that are inherently difficult to compare, a fragment-wise analysis can be expected to be more reliable.

Presented results also hint that a careful score matching techniques are needed if using level two and level three features in the recognition of fingerprint fragments of various sizes. Since the distinctiveness of the level two and level three features changes with the considered fingerprint area, the corresponding matching scores should be appropriately weighted when calculating the ultimate similarity measure in the verification process.

Our study does not claim statistical significance at any confidence level due to a scarce number of compared fingerprints (due to limited database size), we merely report consistent tendencies found in the collected data. We intend to extend this study by the analysis of the statistical distribution of the accord and discord scores, in order to test the results for statistical significance. The next step to take will be to test our findings on a larger database and apply them in a complete fingerprint recognition system.

4.1 Additional remarks concerning the interpretation of the results

Due to the limited number of pair-wise comparisons between fingerprints and the size of the available database caution must be exercised when generalizing the results of the presented experiments. In particular, two issues must be addressed.

Firstly, the factual number of comparisons between the fragments of the same fingerprint varied greatly with the considered fragment size. Namely, there were significantly more comparisons made between small than large fragments. The reason for this was that one can select only a limited number of little-overlapping, large fragments of the same fingerprint. Therefore an estimation of the distribution of both accord and discord scores was impossible – for this reason we do not present the variances – the variances of the score data for large fragments are not meaningful and not comparable to the variances for small fragments. Our future work will address this issue.

Secondly, there exists a significant difference in the mutual distinctive content between fragments of the same size index. For large fragments of the same fingerprint used in separate comparisons there exists an overlap. This makes the mean estimation of match scores reliable for the given pair of fingerprints selected for comparison. At the same time, however, it makes it impossible to compare the variance of the match scores between data collected for fragments of different area size index of the same compared fingerprints. This deficiency can be rectified by re-running the experiment on a larger volume of fingerprints, which will be included in our future work.

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