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# Fingerprint Pre-Classification Using Ridge Density

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**Abstract.** Fingerprint ridge frequency is a global feature, which is most prominently different in fingerprints of men and woman, and it also changes within the maturing period of a person. This paper proposes the method of fingerprint pre-classification, based on the ridge frequency replacement by the density of edge points of the ridge boundary. This method is to be used after applying the common steps in most fingerprint matching algorithms, namely the fingerprint image filtering, binarization and marking of good/bad image areas. The experimental performance evaluation of fingerprint pre-classification is presented. We have found that fingerprint pre-classification using the fingerprint ridge edges density is possible, and it enables to preliminary reject part of the fingerprints without heavy loss of the recognition quality. The paper presents the evaluation of two sources of fingerprint ridge edges density variability: a) different finger pressure during the fingerprint scanning, b) different distance between the geometrical center of the fingerprint and position of the fingerprint fragment.

**Key words:** fingerprint, ridge frequency, performance evaluation.

## 1. Introduction

Automatic fingerprint recognition technologies currently have wide application for biometric person identification (Finger Technologies Survey, 1999; Jain *et al.*, 1997). The purpose of an identification system is to check matching between the person's fingerprint with all fingerprint records, earlier enrolled and stored in the database. Use of such systems depends on discrepant requirements, first of all, identification reliability, matching speed and system cost. Though many identification algorithms (Jain *et al.*, 1997; Isenor and Zaky, 1986) as well as commercial systems (Finger Technologies Survey, 1999) are proposed, achieving satisfactory fulfillment of all contradictory requirements is still an important problem.

Fingerprint recognition technologies are usually based on the matching of fingerprint minutiae (capillary line endings and bifurcation points). However, correct extraction of minutiae and subsequent reliable matching processes are complex tasks and require a lot of computation time if the fingerprint database is large. Possibility to reduce the fingerprint identification time by using techniques for fingerprint pre-classification are currently widely discussed. They are based on matching of certain global parameters of the fingerprints, like ridge orientation maps (Candela *et al.*, 1995), location of singular points (Kawagoe and Tojo, 1984), and features based on Fourier transform of the fingerprint images (Fitz and Green, 1996), etc. All these classification systems are based on complex features and therefore are time consuming. On the other hand, even elaborated pre-classification systems yield about 10% error rate (Hong and Jain, 1998).

The introduction of pre-classification may degrade the quality of the overall identification system by reduction of the authentic acceptance rate at the same false acceptance rate. If the reduction of performance is unacceptable, the pre-classification step can be used to introduce some order into the matching process instead of excluding the fingerprints from it. For example, the identification system, first, could search for matches among the fingerprints, which were approved by the pre-classificator and, if it doesn't found the match, then the input fingerprint is matched with the rest fingerprints. If the probability to find match in the first group of fingerprints is high and the percentage of excluded fingerprints is sufficiently large, then the ordering of matching process can substantially reduce the average identification time without any degradation of the system reliability.

Consequently, it is worth to search for a classification algorithm, which is sufficiently fast and effective. The fingerprint ridge frequency (or equivalent distance between the ridge centers or ridge period value) is yet another global feature, which differs most prominently in the fingerprints of men and woman, and it also changes within the maturing period of a person.

Some authors propose to use this feature for the estimation of the fingerprint filter parameters (Hong *et al.*, 1998; O'Gorman and Nickerson, 1989), and in heuristic algorithms for removal of extracted fingerprint minutiae (Xiao and Raafat, 1991). In the paper by Hong *et al.* (1998) the ridge frequency is estimated by the following procedure:

1. The image is divided into blocks for subsequent evaluation of the average ridge frequency in each block.
2. An oriented window is defined for each block, its orientation coincides with the average directions of the ridges in the block.
3. $x$-signature, i.e., projection of block pixels to the $x$-axis, which is perpendicular to the ridge direction, is calculated for the oriented window. If the block does not contain minutiae or singular points, the form of the $x$-signature is close to a discrete sinusoid with frequency corresponding to the ridge frequency in the window.
4. If the block contains minutiae, singular points, or noise, the shape of the $x$-signature is significantly different from the sinusoid. In this case, the ridge frequency in the block is determined by interpolating the frequency values in the neighboring blocks where they are well defined.

In the recent paper by Kovacs-Vajna *et al.* (2000) two other methods for calculating the fingerprint ridge distance are discussed. First of them uses a geometrical approach for the ridge distance evaluation, while the second one uses a spectral approach and a discrete Fourier transform. Both methods are applicable to gray-scale fingerprint images, therefore the calculated different ridge distances in the sub-blocks can be used to enhance image filtering as well as to remove false minutiae.

All three methods estimate ridge frequency only in some sub-blocks of the original image. If the ridge frequency in the block cannot be estimated reliably, it should be interpolated using the values from the neighboring blocks. However, the interpolation procedure is not a simple task, since in some cases the current block may have no close neighboring blocks with well-defined ridge frequencies.

Although all mentioned techniques of local ridge frequency evaluation were designed for other purposes, it is not too difficult to propose a method allowing to combine the frequency values calculated in the sub-blocks in order to obtain the global average parameter, which could be used for fingerprint image pre-classification. The computational complexity is the main drawback of all these techniques and their use to calculate global ridge frequency exclusively for pre-classification purposes can hardly be justified.

We propose a simple method for the ridge frequency evaluation by replacing it with density of the ridge boundary elements. The method works in image areas containing minutiae, singular points or curved capillary lines. We suppose that this pre-classification is to be used after the fingerprint image filtering, binarization and marking of bad image areas. These pre-processing steps are common in the fingerprint matching algorithms (O'Gorman and Nickerson, 1989; Douglas Hung 1993).

This paper is organized as follows. In Section 2 we describe the simple scheme to evaluate the ridge edge density, which does not require fingerprint image sub-division into the sub-blocks, but can be applied on the entire fingerprint image or part of it. In Section 3 we present experimental results, which demonstrate how our method represents the real ridge density of fingerprint, and how ridge density based pre-classification influences the classification speed and reliability. Finally, some results, related to the ridge density variability in the fingerprints of the same finger are presented.

## 2. Evaluation of Ridge Edge Density

The replacement of ridge frequency by ridge edge density is based on the fact that the fingerprint ridge black/white boundary density in the binary image is proportional to the ridge frequency. This is obvious only the case of straight ridges, which are parallel to the grid of the digital image. As discussed in the experimental section, we have found experimentally, that for real fingerprints the correlation between ridge frequencies and boundary densities is very close to 1. Consequently, the ridge frequency can be replaced by the density of the ridge edge points, which does not depend on the ridge orientation and can be easily calculated in the image areas containing minutiae, singular points or curved capillary lines. The edge point density can be calculated by the simple two-step method:

A) labeling of the pixels located next to the edge of the ridge (capillary lines);

B) counting the labeled pixels in the good image area, and calculating the density of the ridge boundary points $G$ by dividing the number of the labeled pixels by the total number of pixels in the good image area.

The edge points labeling in binary images can be produced by virtually any edge detection algorithm (Patt, 1978), provided that the same algorithm is used for all fingerprint images. In order to demonstrate that any reasonable labeling algorithm will work, the simplest one was selected. The labeling is produced by smoothing the binary image with the $3 \times 3$ window and pixels having values between 1 and 254 label the ridge boundaries (in the original image black and white pixels have values of 0 and 255, respectively). It is obvious, that such algorithm works on images with resolution, sufficient to maintain the distance between the adjacent ridges larger than two pixels. On the other hand, even this simple algorithm could be modified to filter random noise. For instance, narrowing the label range from 1–254 to 30–225 makes the labeling algorithm insensitive to random noise of the size of one pixel in the binary images.

Fig. 1 illustrates action of the proposed algorithm. It can be seen easily, that the density of boundary points in the right image (Fig. 1c), which corresponds to fingerprint (Fig. 1a, b) with high ridge frequency is much larger than the density in the left image.

## 3. Experimental Results and Discussion

First of all, in order to use the $G$ value for the fingerprint processing and recognition, correlation between the real ridge density and the $G$ value should be good. Ideally, the $G$ value should be proportional to the ridge frequency according to its definition. However, in reality it will depend on a few pre-processing steps, mentioned earlier, which should correctly eliminate the image area not occupied by fingerprint, and reliably extract the binary ridge image. Therefore, it is interesting to investigate experimentally, how exactly the $G$ value represents the real fingerprint ridge frequency.

For the pre-classification purposes the $G$ value can be important if such pre-classification increases the fingerprint matching speed and improves, or at least, does not reduce the recognition quality noticeably. The experimental evaluation of the influence of the pre-classification on the fingerprint identification speed and quality is important problem.

Finally, investigation of the factors, which may cause the fluctuations of the $G$ value for fingerprints of the same finger, can be important for correct definition of $G$ value rejection threshold in the pre-classification routine.

The purpose of our first test was to determine the precision of the ridge frequency representation by the $G$ value. The expression of the ridge period in pixel units is justified if all images are scanned with the same resolution. If the same fingerprint will be scanned with different resolutions, then the ridge period length expressed in pixel units will be different, and proportional to the scanning resolution. The ridge frequency is inverse proportional to ridge period and consequently is inverse proportional to scanning resolution. We used this circumstance to simulate the variations in the ridge frequency.

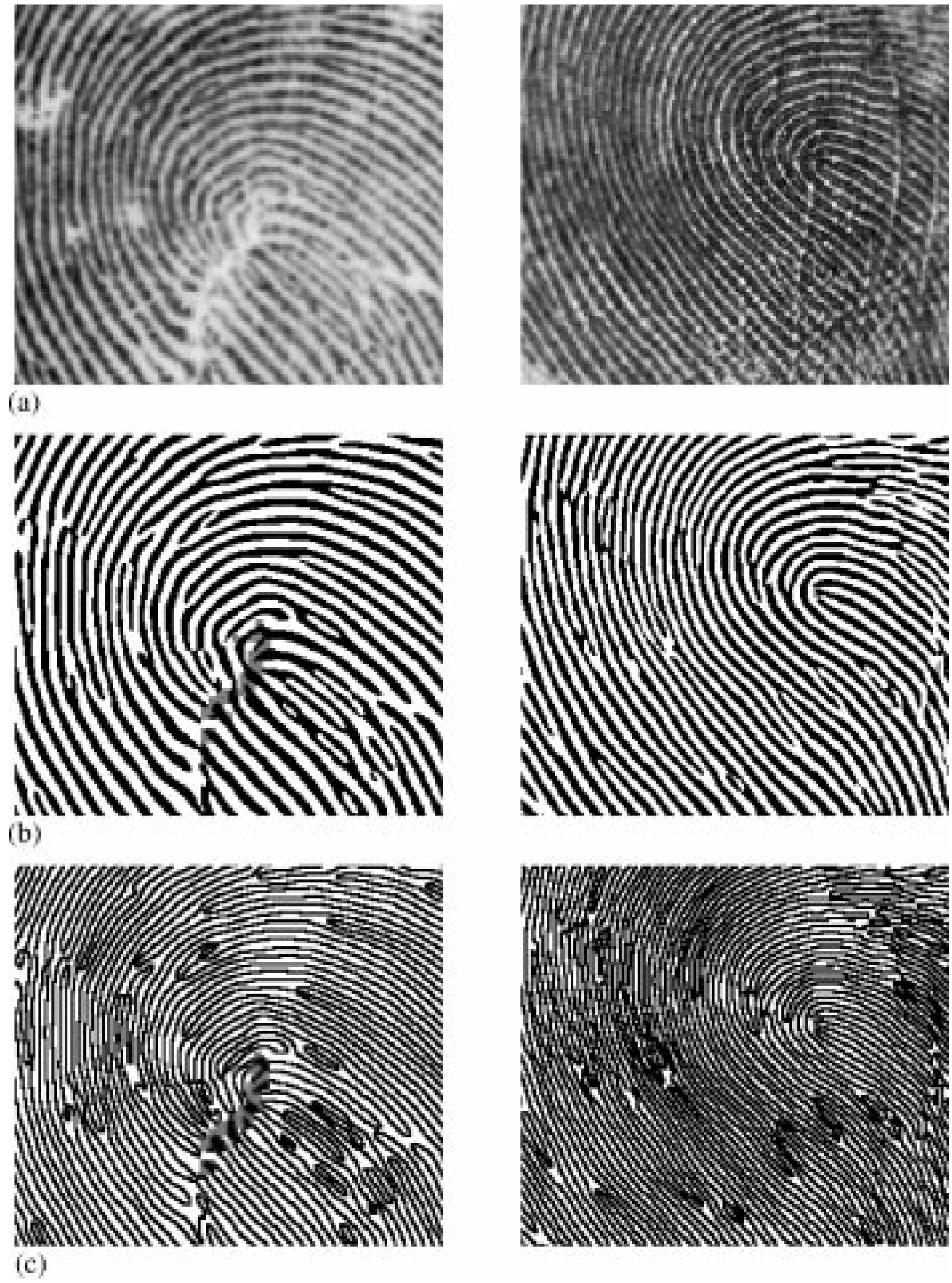


Fig. 1. The steps of determination of the ridge in fingerprints with low (left column) and high (right column) spatial frequency. (a) – the original image, (b) – filtered and binarized image with extracted bad areas, (c) – extraction of the capillary line boundaries, the boundaries are marked by black lines.

Several fingerprint images were scanned with fingerprint scanner at 600 dpi resolution, and subsequently were diminished in the resolution from 500 dpi down to 300 dpi in steps of 20 dpi. Each image produced this way was filtered, binarized, and bad areas were identified. Then, the $G$ value was determined for the entire fingerprint image using the algorithm, described above. The results obtained for four fingerprints are presented in Fig. 2. As can be seen from the figure, correlation between the image resolution and the $G$ value is very high (between 0.9977 and 0.9997 for the tested samples) and the regression curve slopes are the same for all fingerprint images.

The purpose of the second test was to determine how the pre-classification based on the ridge density influences the reliability of fingerprint identification. For this we used fingerprint database, captured with COMPAQ optical fingerprint scanner. The set contains 450 fingerprint images belonging to 9 different persons (i.e., 5 fingerprints of each finger). Quality of the fingerprint images in our database ranges from good to poor.

The description of the fingerprint identification algorithm used in our experiments is not yet published. The image pre-processing algorithm includes the pre-smoothing and contrast standardization, direction field estimation, bad area extraction, smoothing using directional windows, binarization and skeletonization stages. The fingerprint minutiae (ends and bifurcations of the capillary lines) are extracted from the skeleton image. By using certain heuristic rules, some extracted minutiae are removed as erroneous features. During the enrollment procedure the extracted set of features is written to the database. During the fingerprint identification process these sets of features are read from the database and compared with the set of features of the actual fingerprint. According to the comparison scheme "all with all", we had 202500 comparisons. From these, 200250

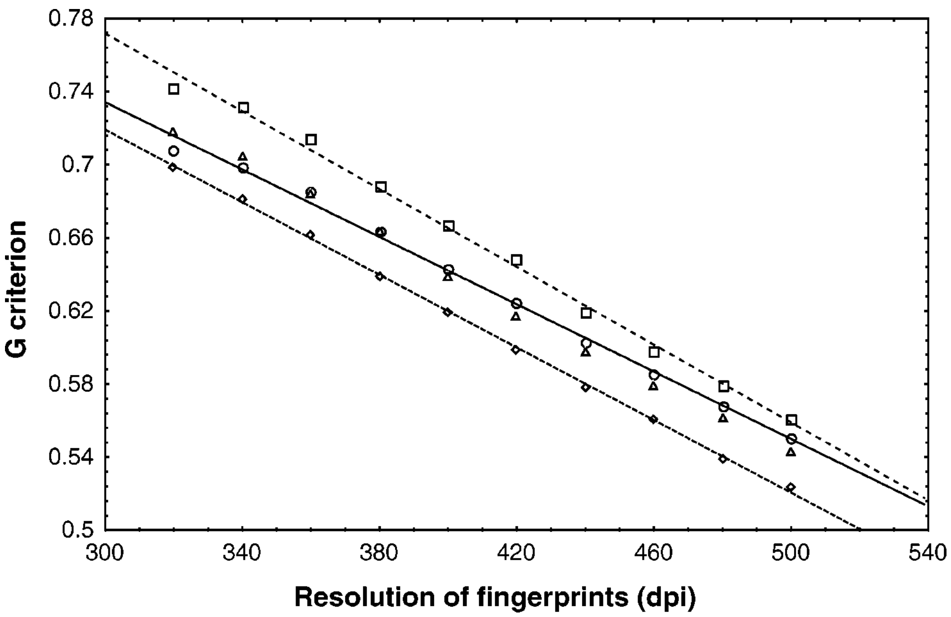


Fig. 2. The $G$ criterion versus the resolution of the fingerprint image. Each line represents one fingerprint test.

comparisons of fingerprints belonging to different fingers, and 2250 comparisons of fingerprints of the same finger were performed.

At the enrollment procedure the $G$ value is calculated for each processed fingerprint, and is written to the database. During the fingerprint matching, the $G$ value of the actual fingerprint is compared with the $G$ values of the reference fingerprints. If the absolute value of the difference between the $G$ values is more than the chosen threshold $T$, the fingerprint similarity is defined as zero. Otherwise, the fingerprint registration, which eliminates relative image translation and rotation is performed, and fingerprint matching score is deduced by comparison of two minutiae sets.

The final fingerprint identification was accomplished by selecting the matching threshold, and classifying the fingerprints with the matching score exceeding the threshold, as belonging to the same finger. Different matching threshold levels give different classification errors rates, namely, false acceptance and false rejection rates. The changes of classification error rates at different matching threshold levels usually are presented as *receiver operating curves* (ROC) (Hong et al., 1998). Different points of ROC express the authentic acceptance rate ($=100\%$ – false rejection rate) and the false acceptance rate at different matching threshold levels.

Fig. 3 illustrates the influence of the ridge density-based pre-classification on the fin-

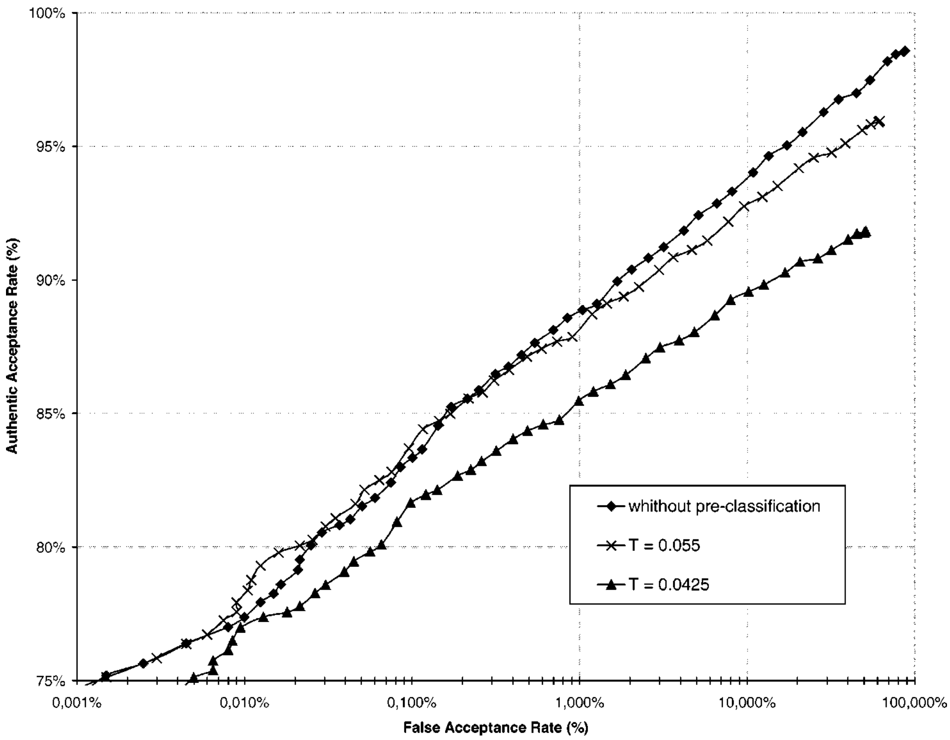


Fig. 3. Receiver Operating Curves, showing the identification performance without and with fingerprint pre-classification based on ridge boundary density.

gerprint recognition quality. The figure shows experimentally obtained ROCs with and without pre-classification at different values of $T$. As can be seen from the figure, for $T = 0.055$ the true acceptance rate obtained using pre-classification is similar, or even higher than the rate obtained without pre-classification, at the same level of false acceptance rate. This is especially evident when comparing true acceptance rates at low false acceptance rates. For example, at false acceptance rate equal $0.01\%$ the true acceptance rates are $78\%$ and $79\%$ for identification without and with pre-classification, correspondingly. At $1\%$ false acceptance level, true acceptance rates are about $88\%$ in both cases.

In the third test, we have investigated how many fingerprints can be rejected from matching process by the pre-classification. For this, during “all with all" comparison, the fingerprint rejections obtained from the ridge edge density comparisons were counted. Fig. 4 illustrates the dependence of rejection rate on $T$ values. As can be seen from the figure, the pre-classification can reject $28\%$ of the fingerprints at $T = 0.055$ level and about $41\%$ at $T = 0.0425$ level (the recognition quality at these $T$ values are shown by corresponding curves in Fig. 3). It should be mentioned, that preliminary $28\%$ and $41\%$ rejection rates can increase the matching speed by 39% and 69%, respectively.

If we impose a restriction on the fingerprint identification with pre-classificator not to change the true acceptance rate at the selected low false acceptance rate, then about one third of fingerprints will be rejected from the matching process (Figs. 3, 4; $T = 0.055$). This indicates relatively large variability of the $G$ value when it is calculated for fingerprints of the same finger. The experimental evaluation of the contribution of some factors to this variability can help to find the ways to reduce it.

One of the main reasons of ridge frequency variability in the fingerprints of the same finger can be nonlinear fingerprint deformation during the scanning procedure. We have investigated how local fingerprint ridge density depends on the distance between the geometric fingerprint image center and the fingerprint fragment. We have also investigated

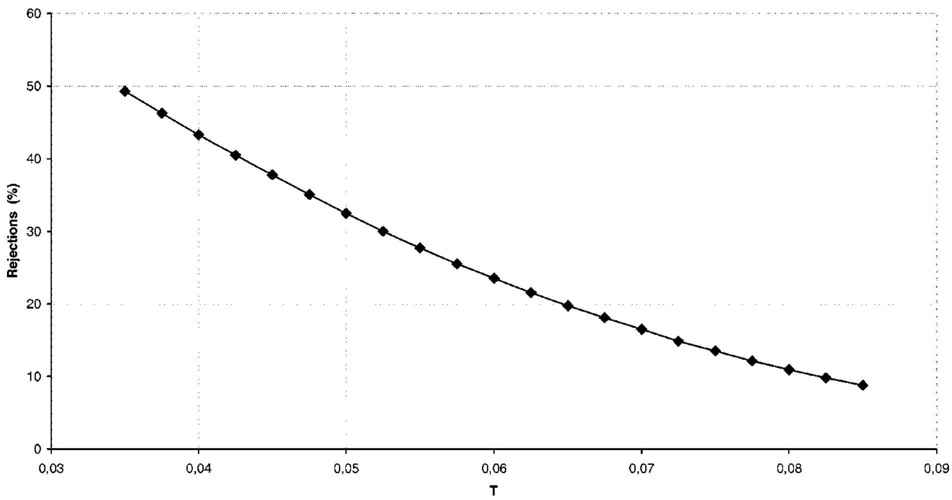


Fig. 4. The dependence of fingerprint rejection percentage on the threshold $T$ level.

how such differences of the ridge density depends on the finger pressure to the scanner window during the scanning procedure. For our tests we used fingerprint database scanned with COMPAQ fingerprint scanner. We have scanned three series of 20 fingerprints of the same finger at weak, medium and strong finger pressure on the scanner window. The pressure was controlled subjectively, and this caused the variations of actual pressure within the same group. According to the persons, who participated in the experiments, it was especially difficult to distinguish between the weak and the medium pressure. For each image, we have calculated good image area, and then calculated the position of the geometric center of this area. In the good area we have calculated the local ridge density $G(K)$ in concentric rings at various distances $K$ from the center.

The averaged results are presented in Fig. 5. As it can be seen from the figure, increase in the finger pressure decreases local $G(K)$ for all distances from the geometric fingerprint image center. At the same time, local ridge density in the rings decreases with the increase of distance from the center. The global density $G$, which is weighted sum of local $G(K)$ values, conforms this tendency. The differences between the average $G$ values, were statistically significant ($G$ equal to 0.57, 0.56, and 0.54 for the groups with the weak, medium and strong pressure, respectively). These results reveal that the pressure strength during fingerprint scanning process can cause the variability of the $G$ value and the control of the pressure strength could improve the pre-classification results. The spatial inhomogeneity of local $G(K)$ values may be another source of the $G$ value variability. The calculations revealed that the variances of all local $G(K)$ within one pressure group are approximately the same as the variance of global $G$ value. Consequently there is no possibility to reduce the variability of $G$ value by narrowing the fingerprint area, which is used to calculate the $G$ value.

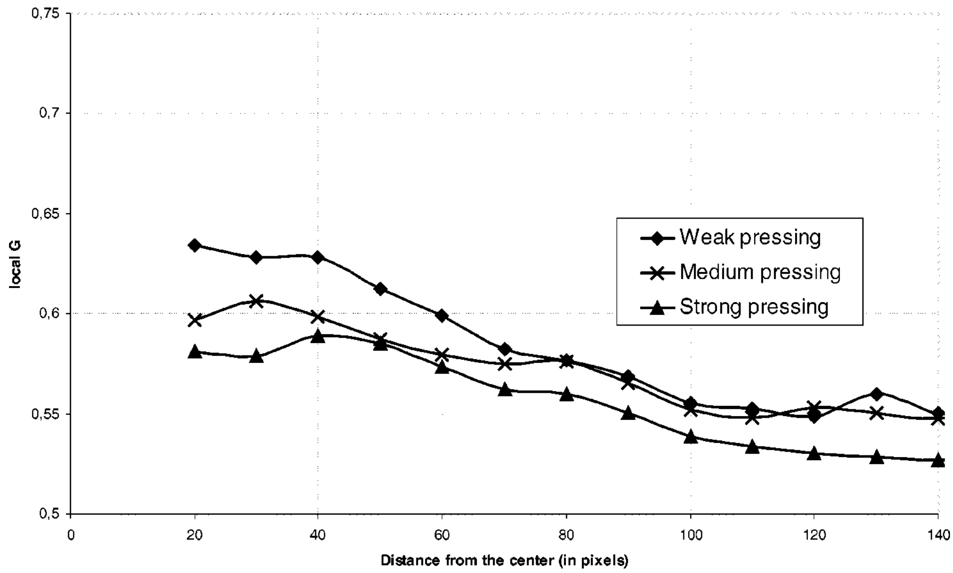


Fig. 5. Dependence of the average local $G_L$ value on the distance from the geometric center of the fingerprint.

## 4. Conclusions

We propose the simple method for the evaluation of the fingerprint ridge frequency by replacing it with ridge edge density. The method does not require preliminary fingerprint sub-division into sub-blocks and allows to evaluate directly the ridge frequency in image areas containing minutiae, singular points or curved capillary lines. We have found that fingerprint pre-classification using the fingerprint ridge density is possible, and, preliminary, it enables to exclude from the matching process about 28% – 41% of the fingerprints without heavy loss of identification quality. This way, the fingerprint matching speed can be increased by 39% – 69%. We have found that finger pressure to the scanner during the scanning process influences strongly the density of the fingerprint ridge edges. The dependence of the local density of the fingerprint ridge edges on the distance from the geometric fingerprint center also shows importance of nonlinear fingerprint deformations on the variability of the density.

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## Pirštų antspaudų klasifikavimas pagal kapiliarinių linijų tankį

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Darbe pateiktas pirštų antspaudų klasifikavimo metodas, naudojant kapiliarinių linijų tankį ir pateiktas eksperimentinis tokio klasifikavimo rezultatų įvertinimas. Parodoma, kad toks klasifikavimo būdas leidžia preliminariai atmesti dalį lyginamų pavyzdžių, neprarandant atpažinimo tikslumo. Darbe pateikti eksperimentiniai duomenys apie kapiliarinių linijų tankio priklausomybę nuo piršto prispaudimo stiprumo skanavimo metu, taip pat nuo fragmento atstumo iki geometrinio piršto antspaudo centro.