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Direct pore-based identification for fingerprint matching process

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Abstract: Fingerprints are one of the most important scientific proof instruments in solving forensic cases. Identification in fingerprints consists of three levels based on the flow direction of the papillary lines at the first level, the minutiae points at the second level, and the pores at the third level. The inadequacy of existing imaging systems in detecting fingerprints and the lack of pore details at the desired level limit the widespread use of third-level identification. The fact that fingerprints with images based on pores in the unsolved database are not subjected to any evaluation criteria and remain in the database reveals the importance of the study to be carried out. In this study, different from classical fingerprint identification methods, a direct pore-based identification system for fingerprint matching is proposed with the dataset created by using the Docucenter Nirvis device and Projectina Image Acquisition-7000 software as a hyperspectral imaging system where pores were visualized more clearly. Although difficult from an operational perspective, the pores in the 800 fingerprints in the database were manually marked for the accuracy of the results. Next, by using a scoring based on iterative closest point algorithm, latent fingerprints were found. Results suggest that the higher the number of pores examined and the more accurately the pores were marked, the higher the hit score. At the same time, query results showed that the scores of other sequential fingerprints in the database which came after the matching fingerprint were even lower.

Key words: Fingerprint, latent fingerprint, third level features, pore, poroscopy, identification

1. Introduction

Fingerprint, an instrument of scientific proof in solving forensic events, plays a very important role in revealing criminals. The identity of the suspect person is determined through the analysis, comparison, evaluation, and verification processes related to the fingerprint [1]. With increasing security issues, automatic fingerprint recognition systems are widely used in crime prevention and detecting criminals [2, 3].

Fingerprint identification is based on features such as minutiae, pores, and papilla unit thickness, which are the line characteristics extracted from fingerprints. These features are defined at three levels in Figure 1.

In the first level of identification, a classification is made in which macro features related to line characteristics are evaluated. In this level, the central region, delta, flow direction, number of lines, and pattern type of the fingerprint are examined [4, 5]. In the second level identification, an evaluation is made according to the relative position and sequences of the line characteristics. Most automatic fingerprint recognition systems are

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based on second-level features since they are stable and distinctive [6, 7]. In the third level identification, small, shaped details on the papilla line, papilla unit thickness, thinness, edge contours, small, shaped details such as wrinkles and scars and the positions of the pores formed by the sweat duct mouths are evaluated relative to each other [8, 9].

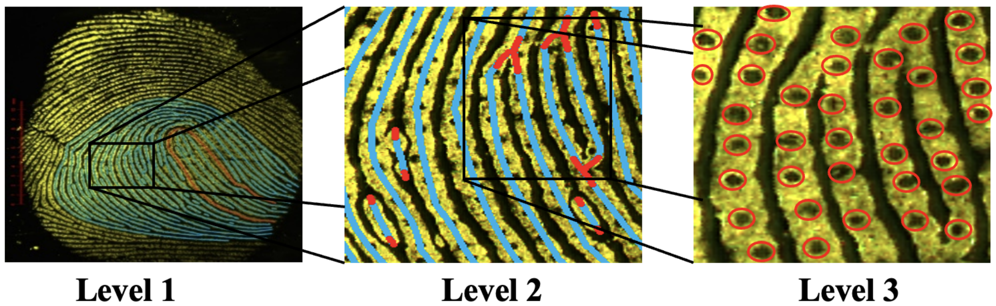


Figure 1. Fingerprint features at Level 1 (general pattern), Level 2 (minutiae), and Level 3 (sweat pores).

When the pores are examined within the scope of the third level identification, it has been revealed that the pores have different shapes and can be single, double, or groups in the form of chains. It has been evaluated that the pore sizes may vary from small to large and may be located in the center or around the papillary line [10]. The pores are located on the papillary line in two ways according to their location. Those with clear borders and located in the middle of the papilla line are called closed pores, while those with no borders located facing the gap between two papillae are called open pores [11].

From the past to the present, the analysis of second-level features has adequately met the need for identification in determining the identity of an individual. The satisfactory level of identification has enabled many academic studies on the automatic fingerprint identification system to focus on second-level features [12]. In fact, the concept of poroscopy has appeared in many publications in the forensic science literature that it may be involved in the identification process. However, these studies could not be put forward as a basis for the courts [13, 14].

Currently, pores are still not being used effectively in the fingerprint identification process. Rather, fingerprint identification systems using second-level features are widely used [15]. As a result of the progress in biometric tools with technological developments, the use of third-level details in automatic fingerprint identification systems has revealed the importance of third-level details in cases where second-level features are not sufficient [16]. It has been emphasized that it is an important requirement to use third-level features to make more precise and strong identification in order to meet high-level security needs [17, 18].

Ashbaugh defined the concept of poroscopy as third-level features around the phenomenon of identification, where quality and quantity depend on several factors [19]. The main reason underlying the limited use of pores is that the images of the third level details cannot be obtained at a sufficient level due to the spatial resolution of live scan devices being much lower than 800 dpi [20]. Third-level identification has become more applicable after it has been developed as an optical resolution ($\geq$1000 dpi) for live fingerprint devices [21]. In parallel with the technological development of optical resolution, with the development of pore-based imaging systems, pores contribute more to the effectiveness of fingerprint identification systems [22, 23]. In addition to these developments, the number of pores and third-level details are considerably higher compared to the number of minutiae makes the analysis results more successful [24, 25].

Fingerprint identification systems currently in use may not always be sufficient for identification [26–28]. This situation causes the number of latent fingerprints in the database to increase day by day. This situation leads to the need to include pore characteristics at different decision-making levels related to fingerprints in decision-making processes [28–30].

Although the presence of at least twelve characteristics in the second level identification does not seem to leave any room for doubt in the decision-making process, a third level identification will make the positive opinion tendencies of the experts stronger by using more details and using up to thousands of pore points [30, 31].

Another important factor affecting the effective use of pores in decision-making processes and identification is the ability to detect qualified fingerprints from the crime scene. In the digital age we live in, it is an undeniable fact to examine and evaluate fingerprints with advanced technical analysis, by detecting more qualified fingerprints with more advanced imaging techniques.

New fingerprint detection and imaging technologies are constantly being developed according to the needs of the field. Unlike traditional optical fingerprint detection systems, fingerprint detection surfaces are scanned by using light sources of different wavelengths (e.g., 460 nm (blue), 530 nm (green), and 650 nm (red)). Here, the surface area where the fingerprint is detected causes scattering and absorption movements depending on the wavelength of the light source. Ultimately, hyperspectral imaging technology is considered to provide better quality fingerprint detection compared to conventional optical sensors [32].

Today, where more precise evidence is needed to clarify the crime, this study detects fingerprints with hyperspectral imaging, which enables more qualified fingerprint detection. It is aimed to present a scoring system based on pore-based matching, using the iterative closest point algorithm, which is based on third-level identification.

2. Materials and methods

In this research, fingerprints were taken in an accredited laboratory environment and a total of 1050 plain fingerprint samples were used from 105 donors who signed a consent form. Volunteers (aged 26–42 years old) were determined from 95 male and 10 female laboratory workers without any disease. They were asked to wash their hands with soap to remove the contaminants, and then dried their hands in the air. Twenty x 10 cm images of fingerprints left on mirror plates specially prepared for the study in size of 13.2x magnification and 530 nm lumi light source were taken by using Projectina Image Acquisition (PIA)-7000 software with Projectina Docucenter Nirvis Hyperspectral Imaging System (Spectral range 350–1100 nm). The main purpose of choosing the mirror as the surface on which the fingerprints are taken is to try to measure the efficiency of the algorithm used at the highest level by taking the clear image of the pores.

Ethics committee decision was taken for our study from Istanbul Technical University Health and Engineering Sciences Human Research Ethics Committee (ITU-SM.INAREK) on 15.02.2022 with the approval number of ITU-SM.INAREK-2022-03.

From 1050 fingerprints, a database was created from 800 plain fingerprints which was evaluated to have a sufficient level of pore quality and detail. Fingerprints with a low number of features and low quality were considered insufficient and excluded from the research. The system was implemented by using MATLAB R2021a [33]. The flow chart of the entire process in the experiment is shown in (Figure 2).

Before taking fingerprints from the donors, their hands were cleaned under appropriate conditions, taking into account the sensitivity that there was no contamination on their hands. While fingerprints were being taken, moderate pressure was applied to the mirror surface to get the ideal image. 800 fingerprints taken from 105 donors and selected from 1050 fingerprints in the dataset are different from each other.

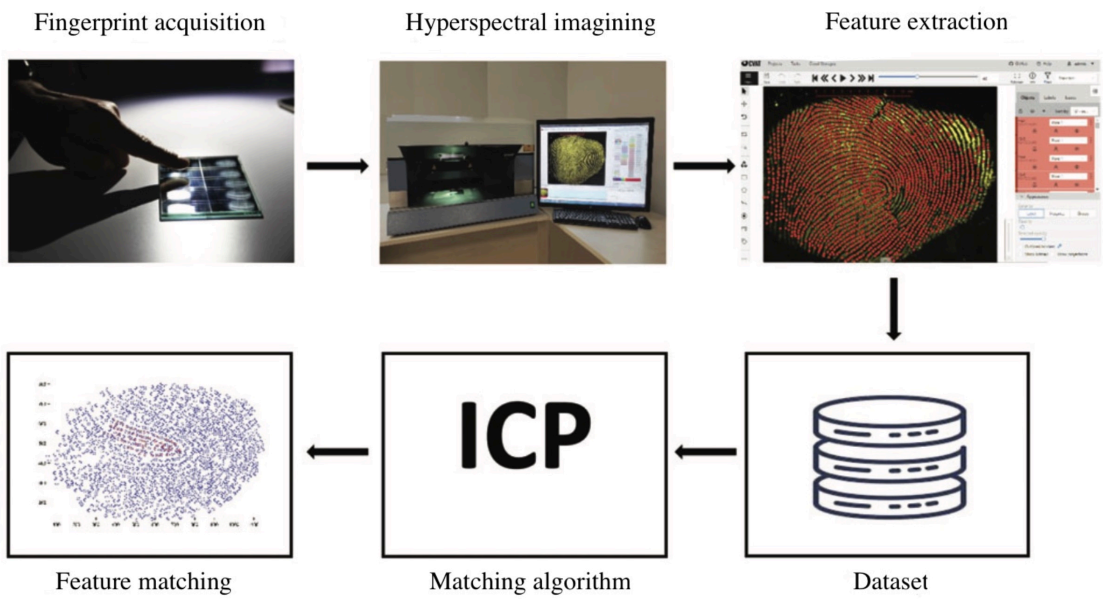


Figure 2. The process followed in the experiment.

2.1. Validation of the database

For the validation of the fingerprints that we used in the database, we randomly selected 10 fingerprints from 1050 fingerprint datasets. Subsequently, we compared the four pore-based plain fingerprints cross-section images of a fingerprint, taken one day apart, in terms of time and distortion, and afterward, we shared the image that 1 of the 10 selected fingerprints in Figure 3. We have observed that the positions of the pores have not changed, and they are all actively existing. However, we cannot say this validation process in the same way for latent fingerprints, especially when evaluating the contribution of third-level features in the identification process, we should pay attention to the changes that may exist on latent fingerprints.

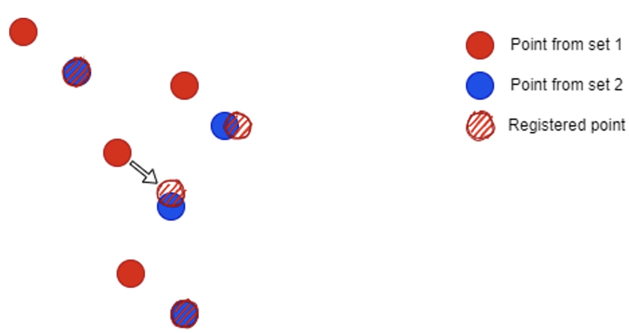


Figure 3. Illustration of the ICP algorithm. The sketch version of the red dots is estimated positions of registered points.

2.2. Creation of database and marking of pores

The main issue taken into consideration while creating the dataset was the presence of fingerprints with few second-level features in the AFIS systems database of unidentified latent fingerprints, and the presence of sufficient number of pore characteristics on the papillary lines of these fingerprints for third-level identification.

Moreover, with the study, it is desired to eliminate the hesitations among the candidates who came after the AFIS query rather than querying the entire dataset with the pore-based approach.

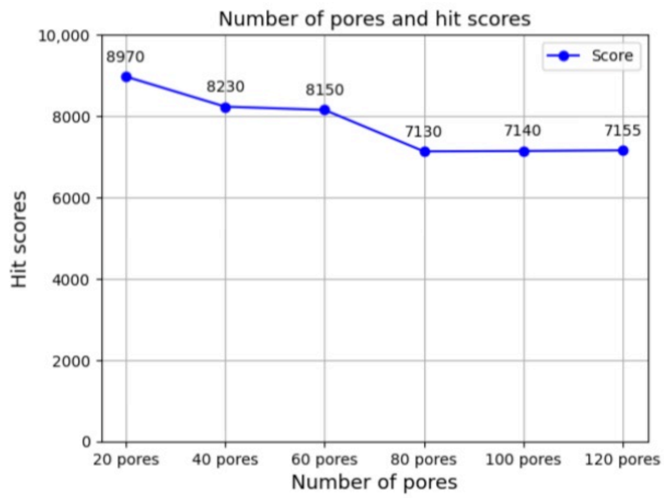


Figure 4. The second hits scores.

The fingerprints taken, sequentially, were automatically scanned in the entire spectrum first on the Projectina Docucenter Nirvis Hyperspectral Imaging Device. The imaging of the pores was provided at the most appropriate light source and wavelength, and then fingerprints with images of the pore characteristics were scaled one-on-one. Within the scope of the protection of personal data, all fingerprints in the database were anonymized by giving a sequence number for each donor and visualized as shown in Figure 4.

The coding process was carried out by marking the pores on all fingerprint images with the Computer Vision Annotation Tool (CVAT) program in the database we obtained (Figure 5). As a result of this coding process, two-dimensional coordinate information of the pores of each fingerprint was obtained.

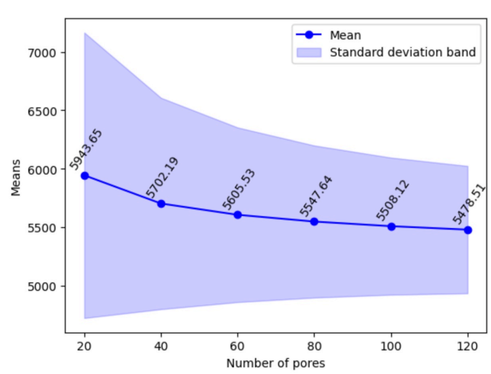


Figure 5. Graph of score-based mean and standard deviations data.

2.3. Matching algorithm

Each marked pore was accepted as a point in the two-dimensional plane and the iterative closest point (ICP) algorithm was used to compare the two fingerprints [34]. Iterative closest point basically tries to find the correspondence of each point by minimizing the error between two different point cloud clusters. In scoring the match rate, the distances between the aligned points obtained as a result of the use of the ICP algorithm and the pore points of the fingerprint corresponding to the latent fingerprint in the database were used as the error score. These error scores were distributed linearly between 0 and 10,000 points and the matching rate of each fingerprint was scored.

Iterative closest point basically determines the rotation and translation matrix between two different point sets. It minimizes the Euclidean distance between the sets using the singular value decomposition (Figure 6). For two different point sets, the singular value decomposition (SVD),

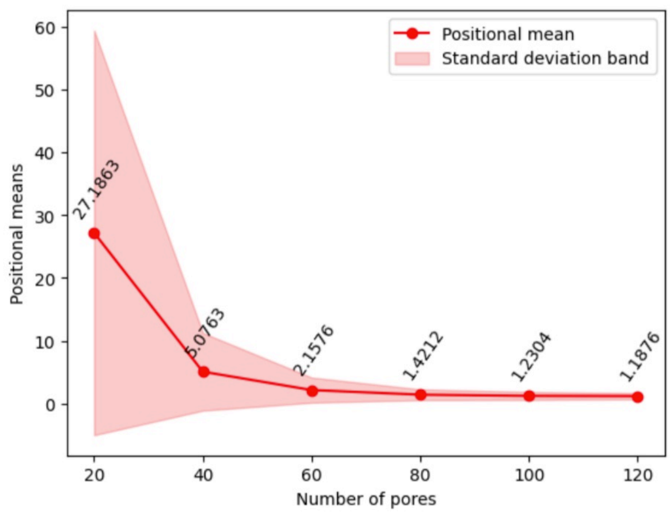


Figure 6. Graph of score-based positional mean and positional standard deviation.

$$P_1 * P_2 = USV, \tag{1}$$

where P_1 and P_2 are the points which represented in the first and second points sets, respectively. In the SVD, U is an $m\ x\ m$ complex unitary matrix, S is an $m\ x\ n$ rectangular diagonal matrix with nonnegative real numbers on the diagonal and V is $n\ x\ n$ complex unitary matrix. The rotation at iterative closest point defined as

$$R = UV', \tag{2}$$

where matrix R defines the rotation between points sets P_1 and P_2. And the translation defined as

$$T = \mu_{P_1} - \mu_{P_2}, \tag{3}$$

where μ_{P_1} and μ_{P_2} are the mean of the coordinates of the points in the point sets P_1 and P_2, respectively.

With the help of 1, 2, and 3, rotation and translation are calculated. After implementation of ICP algorithm, expected locations of points from set 1 represented as registered points in Figure 6. Registered points almost match to points from set 2 [34].

2.4. Creation of latent fingerprints and finding the threshold value

In this research, the fingerprint no. 127 randomly selected from the database was determined as the latent fingerprint. In order to determine the threshold value of the pore amount to be used in the database query, latent fingerprints with 20, 40, 60, 80, 100, and 120 pores were produced in six different point clusters cumulatively marked from the central region.

Threshold value determination was specified based on the hit scores of the sequential matching fingerprints that came after first hit, rather than the hit scores obtained as a result of the database query of the first matching fingerprints.

2.5. Query from the database

2.5.1. Finding the mean and standard deviations

In the light of the data obtained on the threshold value until this stage of the study, all of the 800 fingerprints in the database were automatically marked as 20, 40, 60, 80, 100, and 120 pore groups by the computer to be queried by one to n.

A noise was created both to determine the resistance point of the applied algorithm and to express the losses in the latent fingerprint due to corruptions. A noise was generated by performing a random shift of a maximum of five pixels in the x-y plane at all pores for each point groups. It is claimed to express the distortions that occur in latent fingerprints by noise. The amount of noise was generated randomly. The reaction of the algorithm used with the effect of noise has been tried to be revealed. It is expected that creating more noise will adversely affect the result of the query made from the dataset.

And for each group of points, latent fingerprints were queried by one to n. In other words, a model was established in which the number of pores and the amount of noise are constant, and the latent fingerprint is variable.

As a result of the query, after the noise applied to each group of latent fingerprints (20, 40, 60, 80, 100, and 120 pore groups); data on the 'score-based average' and 'standard deviations' of all other latent fingerprints that came after the matching fingerprint were obtained.

Furthermore, as a result of the query, after the noise applied to each group of latent fingerprints (20, 40, 60, 80, 100, and 120 pore groups); data on the "score-based positional average" and "positional standard deviations" the rank of the matching fingerprint, were obtained.

Thus, the effect limits of random noise applied to all fingerprints in the database on the match rate scores of the other fingerprints coming after the first matching fingerprint and the ranking of the matched fingerprint were determined.

2.5.2. Verification of the model

In order to verify the data obtained on score-based mean and standard deviations and score-based positional average and positional standard deviations; in the same way, fingerprints with 20 to 100 pore marks and a random shift of maximum five pixels in the x-y plane were created in the pores. These latent fingerprints were queried in the database of 800 fingerprints.

As a result of the query, it was observed whether the previously determined latent fingerprint number 127 existed within the limits of the mean and standard deviation values obtained from the noisy fingerprints with 20 to 100 pore marks and a maximum of five pixels random shift in the x-y plane in the pores.

3. Results

To find the threshold value of the number of points to be used, six different point sets were evaluated. In order to observe this situation, the results of the second hits with the highest scores after the matching latent fingerprints marked with 20, 40, 60, 80, 100, and 120 pores are shown in Figure 4. The main reason for observing the scores of the second and later hits was to evaluate the effect of the number of marked pores on the difference in the score between the identical fingerprints and the dissimilar hits.

In Figure 4, the scores of the candidates coming after the matching fingerprint are shared. It has been observed in which pore amount the difference in the score between the matching fingerprint and other candidates is higher. As a result, it was desired to determine the pore amount threshold value, which would be ideal for identification, at the point where the level of score difference is higher and the threshold is formed. As can be seen in the graph, it has been observed that the pore number-based score difference between the matching fingerprint and the other candidates has increased since the average level of 100 pores. Based on this result, in our study, 20 and 100 pore numbers were determined as min and max threshold values.

As a result of the query, after the noise applied to each group of latent fingerprints (20, 40, 60, 80, 100 and 120 pore groups); data on the 'score-based average' and 'standard deviations' of all other latent fingerprints that came after the matching fingerprint is as seen in Table 1. Since coincidental match rate is inverse proportional with the number of features, as expected, mean value decreases while the number of pores increases. At the same time, the results are distributed in a narrower range with decreasing standard deviation by showing consistency. The values shown in Table 1, where data with score-based mean and standard deviation are presented, were found to be compatible with the threshold value. According to Table 1, it was observed that the level of score difference between the matching fingerprint and the other candidates increased as the pore amount increased.

The graphical display of the data given in Table 1 is as in Figure 5. As a result of the query, the data

Table 1. Table of data with score-based mean and standard deviation.

Number of pores	Mean	Standard deviation
20	5943.65	1221.55
40	5702.19	904.46
60	5605.53	747.18
80	5547.64	650.85
100	5508.12	586.81
120	5478.51	545.00

obtained regarding the score-based positional average and positional standard deviations of the different latent fingerprints in each fingerprint group after the noise applied are as seen in Table 2. As expected, for fewer number of pores, the positional mean and the standard deviation of the hits increase due to the decrease in features of fingerprint while standard deviation decreases.

The values shown in Table 2, where data with score-based positional mean and positional standard deviation are presented, give us information about candidate rankings. As a result of an inquiry, it has been revealed that if 100 pores or more features are marked, the ranking of the target fingerprint can be in the first place.

The graphical display of the data given in Table 2 is as in Figure 6. The matched fingerprint scoring values of 20 and 100 pore marked latent fingerprints without noise and the pore matching image of the matched fingerprint.

Table 2. Table of data with score-based positional mean and positional standard deviation.

Number of pores	Mean	Standard deviation
20	27.1863	32.19600
40	5.0763	6.18000
60	2.1576	1.9970
80	1.4212	0.85488
100	1.2304	0.63796
120	1.1876	0.49459

In Figures 7–9, evaluations were made on the results of the query regarding the crime scene fingerprint number 127, which was randomly selected in the data set. The matched fingerprint scoring values of 20 and

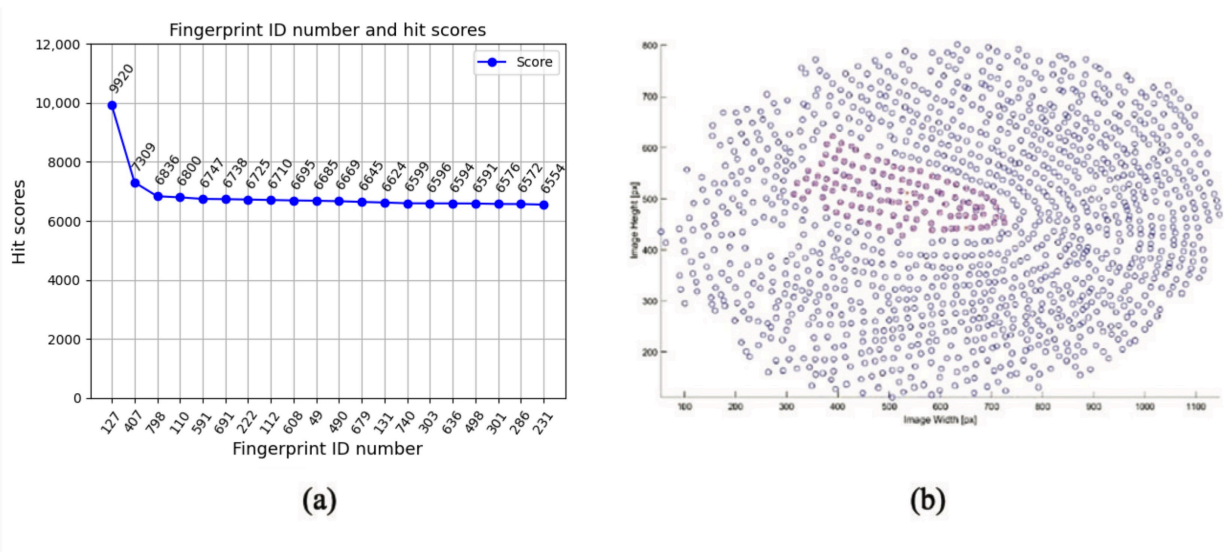


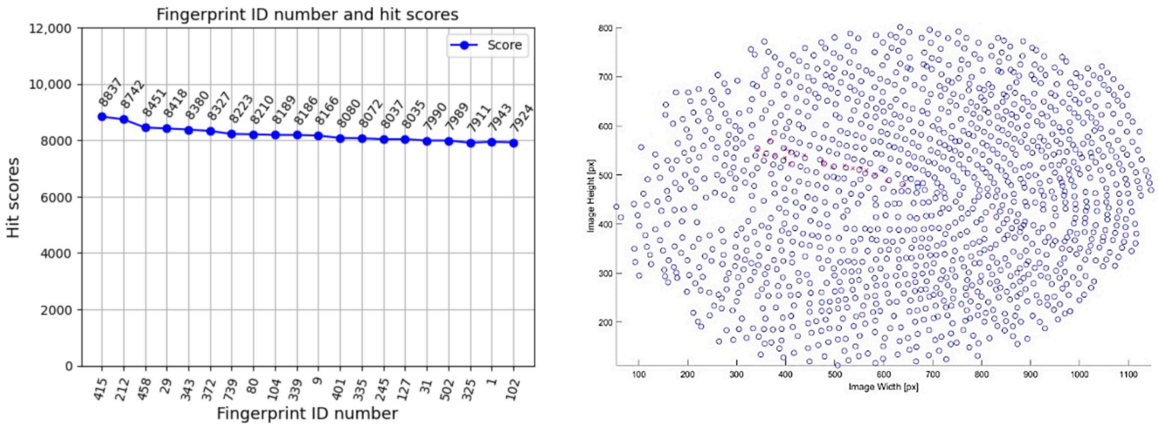
Figure 7. (a) 100 pore-marked first 20 hit list scores, (b) 100 pore-marked pore-matched image without noise.

100 pore-marked latent fingerprints with a maximum random shift of five pixels in the x-y plane and the pore matching image of the matched fingerprint are given in Figures 8 and 9). In Figure 8, after the noise is applied, if 20 pore features are marked in the latent fingerprint number 127, it is revealed whether it changes its place in the candidate ranking. And after the noise was applied, it was seen that the latent fingerprint number 127 regressed to the 15th rank. In Figure 9, after the noise is applied to the latent fingerprint, if 100 pore feature is marked, it is revealed whether it has a positive effect on the candidate ranking. And despite the noise applied, latent fingerprint number 127 appeared to be in the first place again.

4. Discussion

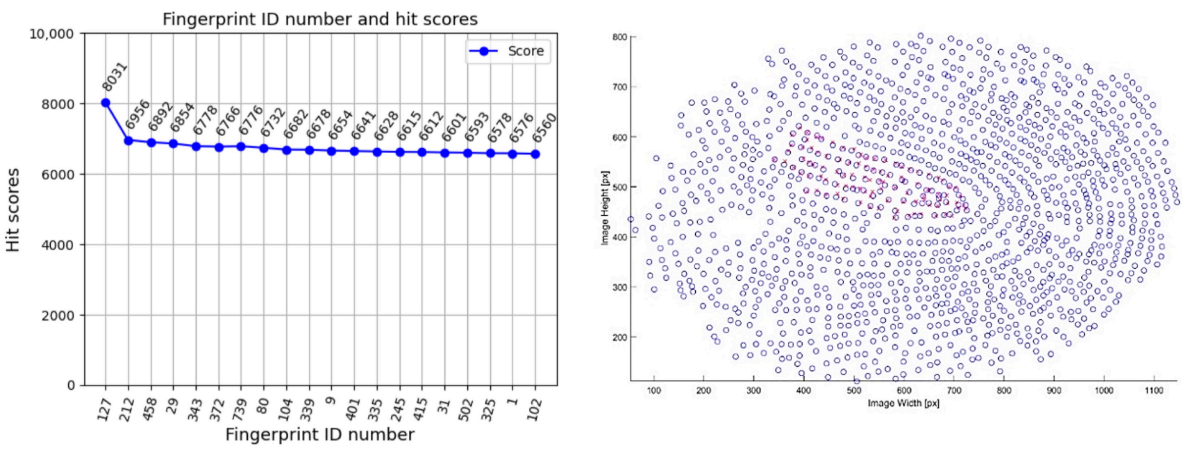
In this study, while creating the database in which latent fingerprints will be queried, unlike classical fingerprinting methods, hyperspectral imaging was preferred in order to get more details in the detection of pores.

In the literature, some algorithms that reveal identification from fingerprints by using direct pore matching have been published [35, 36]. In the light of the findings, a threshold value was specified for determining the amount of pore to be marked first in detecting the latent fingerprint in a third-level identification. By applying



(a) (b)

Figure 8. (a) 20 pore-marked first 20 hit list scores, (b) 20 pore-marked pore-matched image with noise.



(a) (b)

Figure 9. (a) 100 pore-marked first 20 hit list scores, (b) 100 pore-marked pore-matched image with noise.

a fixed amount of noise, the response level of the algorithm against the noise was observed at different pore amounts. After the effect of noise was observed, the amount of pore and the amount of noise were kept constant and all the fingerprints in the database were queried within themselves. After the query, new hits rankings were determined depending on the response of the algorithm to the noise.

In our study, it was observed that the increase and decrease in the scoring of latent fingerprints and fingerprints in the database were directly related to the number of marked pores and the amount of noise. As expected, the hit scores of the second and later fingerprint decreased as the number of marked pores increased. As the number of marked pores decreased, the hit scores of the second and later fingerprint increased. This shows us how important the amount of marked pore is in detecting latent fingerprints.

Considering the high number of pores, different opinions have been put forward about how many pores are required for identification. Ashbaugh has assessed those 20 to 40 pores are sufficient for identification [37].

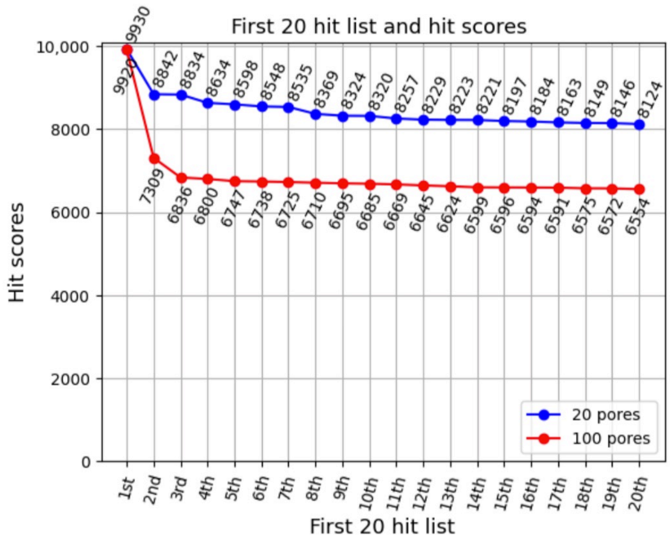


Figure 10. 20 and 100 pore-marked first 20 hit list scores without noise.

In our study, it was observed that latent fingerprints could be detected when 20 pores were marked, but the hit scores of the subsequent fingerprints were also very close to it (Figure 10).

It is evaluated that the presence of hits with a high matching rate after the latent fingerprint, and the small number of marked pores may adversely affect the identification.Besides the number of marked pores, another important factor is the amount of noise related to fingerprints. The amount of noise also directly affects the detection of latent fingerprints.

Therefore, the amount of marked pore and the amount of noise are the most important components in detecting latent fingerprints. While evaluating fingerprints in identification processes, we cannot consider the amount of marked pore and the amount of noise independently of each other.

Ashbaugh, in a study on poroscopy, stated that the physical detection methods used in the detection of fingerprints on the evidence at the crime scene during the identification process adversely affect the visible surface area of the pores, and sometimes it is one of the factors that make the detection of pores even difficult [38]. Therefore, the amount of noise that makes it difficult to detect the pores in the fingerprints negatively affects the resistance coefficient of our iterative closest point (ICP) algorithm-based system.

In our study, the latent fingerprint of the 127th person, whose 20 pores were marked with a maximum random shift of five pixels in the x-y plane, fell to the 15th rank. As a result of the query, the same latent fingerprints marked with 100 pores proceed to the first rank again. From this result, we can see how the amount of noise negatively affects the identification process.

Although the study was conducted hierarchically within the scope of third-level identification, the evaluation we made proceeds independently of first-level classification and second-level minutiae-based identification.

Limitations to the use of pores as an effective identification tool are the lack of guidelines and clear consensus among practitioners regarding the reproducibility, classification, and individuality of pores, and limited research on various aspects of pores [39]. In this case, on the axis of second-level identification, fingerprint experts will be able to independently support opinion trends at different decision levels that they may encounter, depending on the hit score.

If the number of features is 8–12 in the minutiae-based identification process, it is obvious that the fingerprint, which is considered to be matching, is evaluated as weak evidence by the judicial bodies. However, in the cases mentioned, fingerprints evaluated in detail with pore characteristics will be able to be strong evidence.

If the number of Minutiae is <8; contrary to the positive opinion in the first case, in the presence of eight or less papillary characteristics, the negative opinion tendencies of the experts can be strengthened by identification with pore characteristics [40].

As a result, pore characteristics will support opinions in a positive direction in the presence of papil characteristics above 12, while it will contribute negatively to the presence of papil characteristics below 8, and in the presence of papil characteristics below 8–12, it will ensure that fingerprints are a strong means of proof.

5. Conclusion

The study presents an approach based on direct pore matching, independent of the minutiae-based fingerprint matching system, which is the classical method. Although the proposed method works independently of second-level identification, it plays a supporting role in decision scales in second-level identification processes. In addition to this, it provides the opportunity to detect fingerprints whose owners are unknown in databases.

A latent fingerprint that can be used as weak evidence or ignored by saying that it is not suitable for comparison can be used as strong evidence by supporting the fingerprint with enough pore numbers and can be accepted in the courts. It will also assist fingerprint experts in the decision processes of identification operations with positive inclusion and negative exclusion in the evaluation of latent fingerprints.

In future studies, we will conduct research on methods that will use different algorithms that can perform matching that are more resistant to noise and provide high success with fewer pore numbers. At the same time, we will focus on models that will accurately mark pores automatically in order to speed up fingerprint identification processes.

Conflict of interest

The authors have no conflicts of interest, financial or otherwise.

References

[1] Ashbaugh DR. Quantitative-qualitative friction ridge analysis: an introduction to basic and advanced ridgeology. Chemical Rubber Company Press 1999: 149-163. doi:10.1201/9781420048810

[2] Maltoni D, Maio D, Jain AK, Prabhakar S. Handbook of fingerprint recognition. New York, USA: Springer, 2003.

[3] Ratha N, Bolle R. Automatic fingerprint recognition systems. New York, USA: Springer, 2004.

[4] Jain AK, Chen Y, Demirkus M. Pores and ridges: high-resolution fingerprint matching using level 3 features. IEEE Transactions on Pattern Analysis and Machine Intelligence 2007; 29 (1) 15–27. doi:10.1109/TPAMI.2007.250596

[5] Liu F, Zhao Q, Zhang D. A novel hierarchical fingerprint matching approach. Pattern Recognition 2011; 44 (8): 1604–1613. doi:10.1016/j.patcog.2011.02.010

[6] Labati RD, Genovese A, Muñoz E, Piuri V, Scotti F. A novel pore extraction method for heterogeneous fingerprint images using Convolutional Neural Networks. Pattern Recognition Letters 2018; 113: 58–66. doi:10.1016/j.patrec.2017.04.001

[7] Liu F, Zhao Y, Shen L. Feature guided fingerprint pore matching. In Biometric Recognition: 12th Chinese Conference, CCBR 2017, Shenzhen, China; 2017. Proceedings 12 (pp. 334-343). Springer International Publishing. doi:10.1007/978-3-319-69923-3_36

[8] Khodadoust J, Khodadoust AM. Fingerprint indexing based on minutiae pairs and convex core point. Pattern Recognition 2017; 67: 110–126. doi:10.1016/j.patcog.2017.01.022

[9] Zhang D, Wang W, Huang Q, Jiang S, Gao W. Matching images more efficiently with local descriptors. In: 2008 19th International Conference on Pattern Recognition. IEEE, 2008: 1-4. doi:10.1109/ICPR.2008.4761304

[10] Chatterjee SK. Edgeoscopy. Finger Print Ident. Mag 1962; 44 (3).

[11] Espinoza M, Champod C. Using the number of pores on fingerprint images to detect spoofing attacks. In: 2011 International Conference on Hand-Based Biometrics. IEEE, 2011; p.1-5. doi:10.1109/ICHB.2011.6094347

[12] Pankanti S, Prabhakar S, Jain AK. On the individuality of fingerprints. IEEE Transactions on Pattern Analysis and Machine Intelligence 2002; 24 (8): 1010–1025. doi:10.1109/TPAMI.2002.1023799

[13] Locard E. L'identification des criminels par l'examen des Orifices sudoripares. Poinat 1912 (in French)

[14] Renea RD. Unusual latent print examinations. Journal of Forensic Identification 2003; 53 (5): 531-537.

[15] Ratha NK, Karu K, Chen S, Jain AK. A real-time matching system for large fingerprint databases. IEEE Transactions on Pattern Analysis and Machine Intelligence 1996; 18 (8): 799–813. doi:10.1109/34.531800

[16] Oklevski S, Jasuca OP, Singh G. Poroscopy as a Method for Personal Identification: Issues and Challenges. Turkish Journal of Forensic Science and Crime Studies 2019; 1 (1):39-49.

[17] Zhao Q, Zhang L, Zhang D, Luo N. Direct pore matching for fingerprint recognition. International Conference on Biometrics 2009; 5558: 597–606.doi:10.1007/978-3-642-01793-3_61

[18] He Y, Tian J, Li L, Chen H, Yang X. Fingerprint matching based on global comprehensive similarity. IEEE Transactions on Pattern Analysis and Machine Intelligence 2006; 28 (6): 850–862. doi:10.1109/TPAMI.2006.119

[19] Ashbaugh DR. Premises of Friction Ridge Identification, Clarity, and the Identification Process. Journal of Forensic Identification 1994; 44 (5): 499-516.

[20] Zhang D, Liu F, Zhao Q, Lu G, Luo N. Selecting a reference high resolution for fingerprint recognition using minutiae and pores. IEEE Transactions on Instrumentation and Measurement 2011; 60 (3): 863–871. doi:10.1109/TIM.2010.2062610

[21] Yuan C, Yu P, Xia Z, Sun X, Wu QMJ. 'FLD-SRC: Fingerprint liveness detection for afis based on spatial ridges continuity'. IEEE Journal of Selected Topics in Signal Processing 2022; 16 (4): 817-827. doi:10.1109/JSTSP.2022.3174655

[22] Lee J, Pyo M, Lee SH, Kim J, Ra M et al. Hydrochromic conjugated polymers for human sweat pore mapping. Nature Communications2014; 5 (1):3736. doi:10.1038/ncomms4736

[23] Elsner C, Abel B. Ultrafast high-resolution mass spectrometric finger pore imaging in latent fingerprints. Scientific Reports 2014; 4 (1): 6905. doi:10.1038/srep06905

[24] Lu M, Chen Z, Sheng W. A pore-based method for fingerprint liveness detection. In: 2015 International Conference on Computer Science and Applications (CSA). IEEE, 2017, p. 77-81. doi:10.1109/CSA.2015.79

[25] Liu F, Zhao Q, Zhang L, Zhang D. Fingerprint pore matching based on sparse representation. In: 2010 20th International Conference on Pattern Recognitio. IEEE, 2010: 1630-1633. doi:10.1109/ICPR.2010.403

[26] Chaberski M. Level 3 friction ridge research. Biometric Technology Today 2008; 16 (11-12): 9–12. doi:10.1016/S0969-4765(08)70234-0

[27] Chen Y, Jain AK. Beyond minutiae: A fingerprint individuality model with pattern, ridge, and pore features. In: Advances in Biometrics: Third International Conference, ICB 2009, Alghero, Italy. Proceedings 3. Springer Berlin Heidelberg, 2009: 523-533. doi:10.1007/978-3-642-01793-3_54

[28] Kryszczuk KM, Morier P, Drygajlo A. Study of the distinctiveness of level 2 and level 3 features in fragmentary fingerprint comparison. In: Biometric Authentication: ECCV 2004 International Workshop, BioAW 2004, Prague, Czech Republic, Proceedings. Springer Berlin Heidelberg, 2004: 124-133. doi:10.1007/978-3-540-25976-3_12

[29] Roddy AR, Stosz JD. Fingerprint features-statistical analysis and system performance estimates. Proceedings of the IEEE 1997; 85 (9): 1390–1421. doi:10.1109/5.628710

[30] Vatsa M, Singh R, Noore A, Singh SK. Combining pores and ridges with minutiae for improved fingerprint verification. Signal Processing 2009; 89 (12): 2676-2685. doi:10.1016/j.sigpro.2009.05.009

[31] Zhao Q, Zhang D, Zhang L, Luo N. High resolution partial fingerprint alignment using pore-valley descriptors. Pattern Recognition 2010; 43 (3): 1050–1061. doi:10.1016/j.patcog.2009.08.0044

[32] Rowe RK, Corcoran SP, Nixon KA, Ostrom RE. Multispectral imaging for biometrics. In Spectral Imaging: Instrumentation, Applications, and Analysis 2005; 5694: 90-99. doi:10.1117/12.589487

[33] MathWorks Inc. (2021). MATLAB [online]. Website https://www.mathworks.com/products/matlab.html [accessed 10 05 2021].

[34] Chen Y, Medioni G. Object modelling by registration of multiple range images. Image and Vision Computing 1992; 10 (3): 145-155. doi:10.1016/0262-8856(92)90066-C

[35] Liu F, Zhao Q, Zhang D. Fingerprint pore matching. In Advanced fingerprint recognition: from 3D shape to ridge detail 2020; 165–187.

[36] Liu F, Zhao Y, Liu G, Shen L. Fingerprint pore matching using deep features. Pattern Recognition 2020; 102:107208.

[37] Anthonioz A, Egli N, Champod C, Neumann C, Puch-Solis R et al. Level 3 details and their role in fingerprint identification: a survey among practitioners. Journal of Forensic Identification 2008; 58 (5): 562.

[38] Darshan, GP, Prasad BD, Premkumar HB, Sharma,S. Kiran C et al. Fluorescent quantum dots as labeling agents for the effective detection of latent fingerprints on various surfaces. Quantum Dots Woodhead Publishing. 2023; 539-574

[39] Anthonioz A, Champod C. Integration of pore features into the evaluation of fingerprint evidence. Journal of Forensic Sciences 2014; 59 (1):82-93. doi: 10.1111/1556-4029.12302

[40] Champod C. Edmond Locard. Numerical standards and “probable” identifications. Journal of Forensic Identification 1995; 45(2): 136–163.