A. Brömme, C. Busch, A. Dantcheva, C. Rathgeb and A. Uhl (Eds.): BIOSIG 2019,
Lecture Notes in Informatics (LNI), Gesellschaft für Informatik, Bonn 2019 1

Psoriasis Damage Simulation into Synthetic Fingerprint

Ondřej Kanich[1], David Košťák[1] and Martin Drahanský[1]

Abstract: The goal of this article is to describe method for simulation of damage done by psoriasis. Designed method is based on extracting subjects from real images and then including them into synthetic images. Images are damaged by six different settings. Each setting represents different level of disease severity. Results were verified by visual comparison with real images, consultation with medical doctor, quality measurement methods (NFIQ, FiQiVi), and comparison score (VeriFinger). The most severe damage achieved median score of 38 % (from the reference).

Keywords: synthetic fingerprint, psoriasis, skin diseases, damage simulation, machine learning.

1 Introduction

Skin diseases are relatively common in population (in a general medical practice, there are about 20-25 % of patients with skin complaints [Ka18]), but non-existent in fingerprint databases. With widespread usage of fingerprint recognition technology it is necessary to take these cases into account. Collecting medical and biometric data of patients is difficult. It needs cooperation of medical doctors, biometric technicians and patients. Acquiring fingerprints from patients with severe disease is unpleasant for all of participants. Because all of this it would be beneficial to use synthetic fingerprints with skin disease damage. Large portion of this article is based on [Ka18].

2 Synthetic Fingerprints and Skin Diseases

Synthetic fingerprint is fingerprint generated by software. Input variables for this generation can be diverse. It can be some random points, random minutiae but also full fingerprint template. Generator with some additional information (density, orientation field, class, etc.) creates synthetic fingerprint. This is usually called the **master fingerprint**. This term means fingerprint in perfect condition (without any damage made by environment, user, finger condition or sensor). Usually after that come phases where master fingerprint is damaged, so it looks more realistic (creating several impressions from one master fingerprint). In this article focus will be laid on simulating only one specific damage to fingerprint in the perfect form.

[1] Brno University of Technology, Faculty of Information Technology, Božetěchova 1/2, 612 66 Brno, Czech Republic, ikanich@fit.vutbr.cz, xkosta10@stud.fit.vutbr.cz, drahan@fit.vutbr.cz

2.1 Possibilities for Simulation of Diseased Images

To create the impression of fingerprints having a skin disease it is necessary to implement an algorithm that is designed to damage the master fingerprint and make it look like the fingerprint from a diseased finger. The first method simulates the seven local and five global markings that can be found on the diseased fingerprints [Ba17]. After that, the damage done to a fingerprint with these markings is based on the **probabilistic distribution** of markings in the specific diseases. This way is very dependent on the analysis of the available database, but it can create every disease that is in the database. The second method for creating algorithms that will damage the fingerprints is based on **study of the diseases** one by one. By conducting a thorough analysis of a specific type of damage a unique algorithm can be created. There could even be a few algorithms based on, for example, disease severity. Using the second method will create more precise results for the damage, but only for a few of diseases. Sometimes the effects of diseases are difficult to generalize. In that case, it might be enough to **adapt damage from the existing** fingerprint images to a synthetic one. [DK19]

3 Psoriasis Simulation

To test the third approach, psoriasis was chosen as a sample disease. First the third approach is described more thoroughly. Nowadays the most popular methods for adopting, learning, etc. are neural networks and machine learning. These methods need a lot of input data, but they have incredible results. That why psoriasis was chosen. It is the second most frequent disease in the database. Also, it is one of the most frequent skin diseases. Around 1-3 % of the population suffers from this disease [Bř18]. The database used is not big enough to fully utilize these kinds of methods (e.g. deep neural networks). Nevertheless, the core idea of these methods could still be used.

3.1 Psoriasis

Psoriasis vulgaris is a common, chronic, and inflammatory disease of the skin that is often indistinguishable from a serious form of hand eczema. Psoriasis is caused by a failure of the immune system. It is too active, so skin cells are created not in 28-30 days, but in three to four days. The body is not prepared for such an influx of cells, so the old cells are accumulated on the skin's surface as a result. Itchy, silver flakes known as plaque are created. These dry and scaling plaques covered with dry scales are peeled in layers. The more severe the disease is, the more plaque is created and the more the fingerprint is damaged. [Ba17] [HKD18] [Bř18] [Ke03] [Ko18] [DK19]

3.2 Damage Analysis

The vast majority of fingerprints affected by psoriasis are completely damaged. Ridges

are almost entirely unreadable. The most frequent feature is a large irregular dark spot bounded by a white border. Apart from this feature, the presence of larger dark areas or thick lines is also common, as well as round and oblong spots. [Ba17] [HKD18] [Ko18]

In Fig. 1 the images acquired by the dactyloscopic card are shown. They are ordered by damage severity. In Fig. 1a, only a small white part in the bottom left of the image is damaged. Fig. 1b shows more plaque and more damage. Not only white places are present but also white lines. Inside of some white subjects are black dots. In Fig. 1c, a very damaged fingerprint can be seen. Half of the image is white with black dots and the other half is almost entirely black. There are some remainders of the ridges at the bottom of the image. The last image, Fig. 1d, shows only black noise with some white spaces where the ridges originally were. Because of this great variability of inflicted damage to fingerprints the psoriasis is also good for approach of adopting the damage.

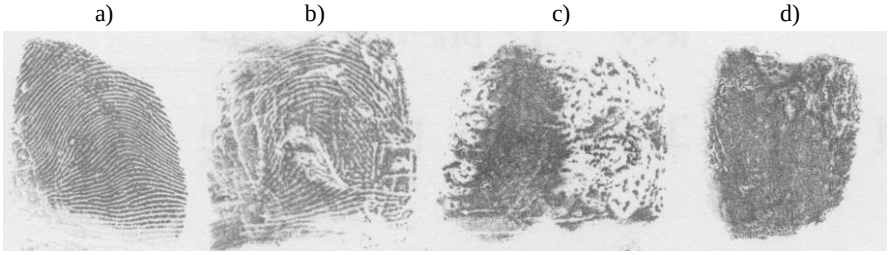

Fig. 1: Different fingerprint affected by psoriasis acquired by dactyloscopic card.

3.3 Design of a Method for Psoriasis Simulation

Based on the described details of the disease, the idea of an algorithm for the damage extraction from existing images can be designed. This consists of the following steps:

1. Load an input (real) image.
2. Detection, extraction, processing, and storage of subjects from the image.
3. Repeat steps 1-3 until there are no input images.
4. Load the synthetic image.
5. Localize the fingerprint area.
6. Load the damage subject and insert subject into the image.
7. Until there is a defined number of subjects in the image, repeat step 6-7.

The idea is to extract subjects (individual damages) from real fingerprint images. That is *step 1*; it loads all images that can be learned from one by one. The image gets a five-pixel border and the background is filled with one color. This image is now ready for *step 2*; the extraction of subjects. This is done by using threshold, color conversion, blur, erosion,

dilatation, and a Canny operator. The three main classes of a subject are defined. *Black subjects* (size 5,000-34,000 px), *small white subjects* (size 370-6,000 px), and *large white subjects* (size 6,000-25,000 px). The size values of different subjects were found out through experimentation. Because the background is filtered, it is relatively easy to take bigger areas in the image as a source of damage. Examples of extracted subjects can be seen in Fig. 2. [Ko18]

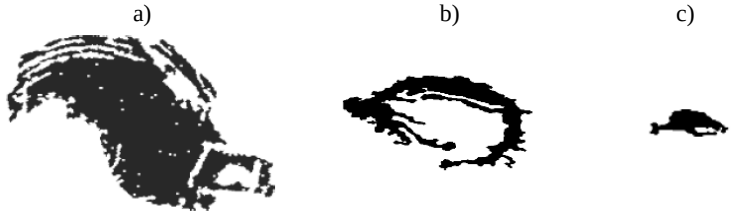

Fig. 2: Enlarged and colored subjects – a) black, b) large white and c) small white subject.

Subjects have their alpha channel set, otherwise their white background color would be used instead of transparency. Because of the possible various image sizes in the input database, all subjects have to be normalized. That is done by using Eq. 1. [Ko18]

$$\text{subject}_{\text{height}} = \frac{target_{height}}{input_{height}} \quad \text{and} \quad \text{subject}_{\text{width}} = \frac{target_{width}}{input_{width}} \tag{1}$$

Subjects are stored in the database. In *step 4*, the target (synthetic image) is loaded. By mapping the non-zero pixels, the area of the fingerprint is localized in *step 5*. In *step 6*, the subject from the database is loaded. Based on the defined number of subjects that should be inserted into the image, the count of each subject class is determined. For the *black subjects* (Fig. 2a) the rules are: defined number ≤ 15 means no subject, ≤ 30 means 1 subject, ≤ 40 means 2 subjects, ≤ 80 means 3 subjects, ≤ 150 means 4 subjects, ≤ 250 mean 5 subjects and > 250 means 6 subjects. For the *larger white subjects* (Fig. 2b), the rules are: defined number ≤ 15 means no subject, ≤ 100 means 1 subject, ≤ 250 means 2 subjects, > 250 means 3 subjects. [Ko18]

For the *small white subjects* (Fig. 2c), the defined number is the count of subjects from that class. Also, this small object is inserted into a random location, but it has to be ensured that the whole subject would be in the fingerprint area. Individual damages could be overlapping. For the black and larger white objects, the following optimization is used. There is a 50 % chance of using a mirror image of the stored subjects (practically doubling the number of subjects available). These subjects are inserted closer to the center of the image. Random coordinates are generated from the interval of 1-90 px for vertical axis and 1-60 px for horizontal axis. Obviously, the whole subject has to fit into the fingerprint area. [Ko18]

For the simpler processing of input images, only one of the acquirement methods was chosen. The chosen method is the dactyloscopic card (as can be seen on Fig. 1 and 2). This

is because more than half of the psoriasis images in the database are from this method. Overall, 174 images of psoriasis from the dactyloscopic card were used to extract subjects. From this input, 122 black subjects, eight large white subjects, and 1,022 small white subjects were extracted.

3.4 Psoriasis Damage Simulation Examples

In this case, six different settings of psoriasis are simulated. The list contains damage name, testing shortcuts, and a short description with settings. The settings for this type of simulation is only the number of subjects inserted into the image. The real images of psoriasis can be seen in Fig. 1 and 2, generated impressions in Fig. 3 and 4. **Small number of subjects (psor0)** 15 subjects generated, the synthetic image can be seen in Fig. 3a. **Small number of subjects plus one black subject (psor1)** 30 subjects generated, synthetic image can be seen in Fig. 3b. **Small number of subjects plus two black subjects (psor2)** 40 subjects generated, the synthetic image can be seen in Fig. 3c. **Moderate number of subjects plus three black subjects (psor3)** 60 subjects generated, the synthetic image can be seen in Fig. 4a. **High number of subjects plus three black subjects (psor4)** 80 subjects generated, the synthetic image can be seen in Fig. 4b. **Enormous number of subjects plus four black and one larger white subject (psor5)** 100 subjects generated, the synthetic image can be seen in Fig. 4c.

Fig. 3: Examples of psoriasis disease damage (a) psor0, b) psor1, c) psor2).

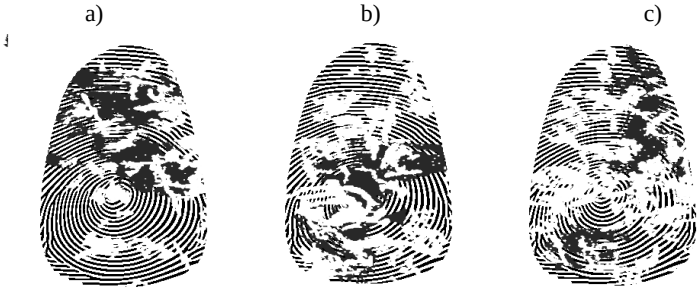

Fig. 4: Examples of psoriasis disease damage (a) psor3, b) psor4, c) psor5).

4 Evaluation

The database of 150 synthetic images from three synthetic generators (SFinGe, Anguli, SyFDaS) were used. Each generator created images with natural fingerprint class distribution. Images were scaled so that their resolution is similar. Three quality measurement metrics are used for the evaluation of the generated images. The standardized *NFIQ* [TWW04] (NIST – National Institute of Standards and Technology, Fingerprint Image Quality) solution, where quality is determined by five classes, where first class is the best quality and fifth being the worst. There is the commercial *VeriFinger* [Ne18] with the comparison score, where damaged fingerprint images and their respective source images are used for verification, is roughly from 0 to 2,250, where the higher number means higher quality (better verification to be exact). The last metric is quality measurement *FiQiVi* based on [Or18], which is an experimental algorithm that is currently being researched. Its range is from 0-100, where 100 signifies the best quality. For each metric there is a graph. Each graph (Fig. 5 - 7) shows minimal and maximal value (red dots) and the median (shown as black dash).

4.1 Evaluation by Specified Methods

Detailed information and example images for the psoriasis damage category are summarized in Section 3.4. The severity of the damage should be sorted out (the higher number in the damage shortcut should mean more severe damage). The choice and position of generated subjects are stochastic, a little bit of volatility in maximal and minimal values can be excepted.

The NFIQ graph (Fig. 5) shows some interesting results. The median values for almost all of the damages, *psor2*, *psor3*, *psor4*, and *psor5* is at the fourth class. *Psor4* and *psor5* even achieved minimal values in the second class.

VeriFinger's comparison score in Fig. 6 shows interesting results. The median values have almost a quadratic distribution. Nevertheless, the extreme minimal value for the *psor1* can be seen. By the similarity of the graphs, it can be said that all quality metrics are sensitive to this kind of damage and that this is why all of them show similar scores and behavior.

The FiQiVi quality metric in Fig. 7 shows small changes in the minimal and maximal

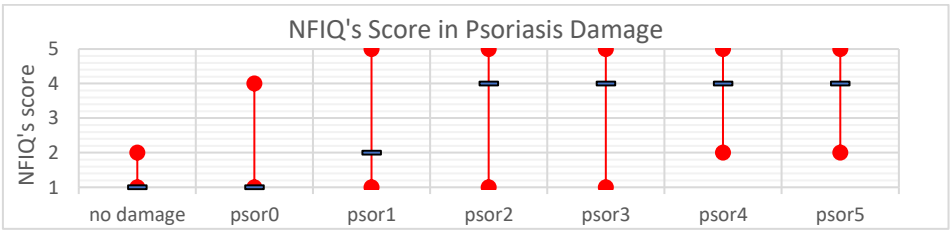

Fig. 5: Graph of NFIQ's score in psoriasis damage.

value which confirms the fact that they are created because of some random effects. As a final note, all damages are lower than the reference no damage values. *Psor5* has its average median scores only 38 % of the reference scores. That is tremendous quality drop.

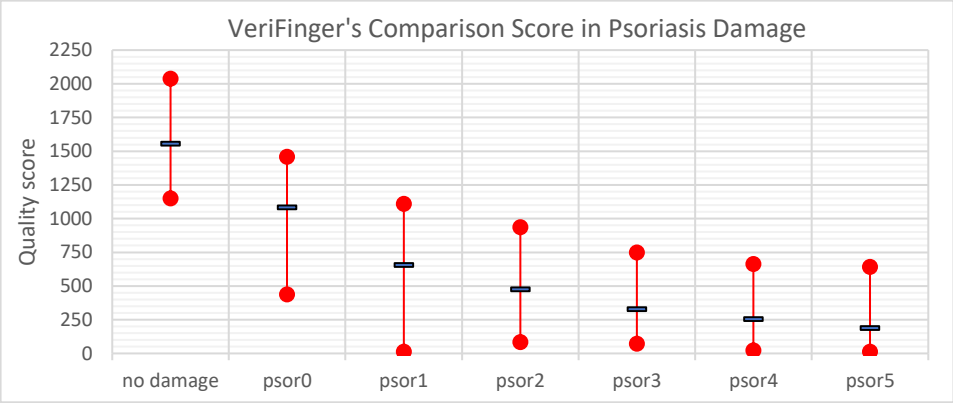

Fig. 6: Graph of VeriFinger's comparison score in psoriasis damage.

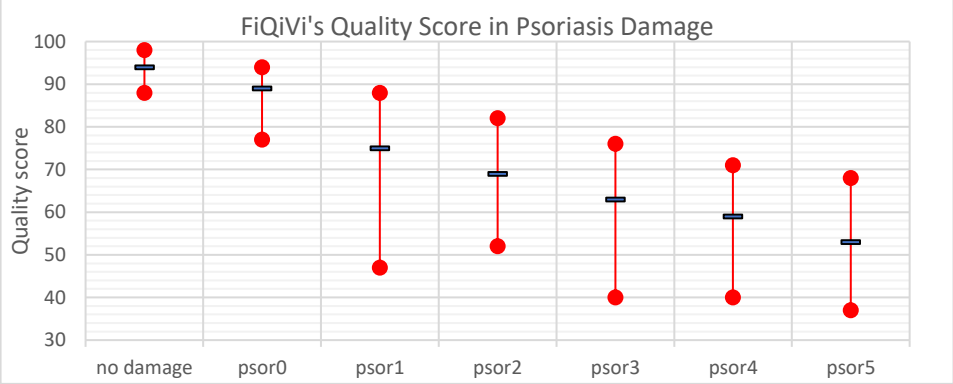

Fig. 7: Graph of FiQiVi's quality score in psoriasis damage.

5 Conclusion

Skin diseases can be a big problem when using widespread biometric systems. The systems that are currently used are not capable of detecting skin diseases or enhancing the quality of fingerprints with diseases, which basically makes the biometric system unsuitable for some users. The main reason is that it is very difficult to obtain access to a database of fingerprints with skin diseases. Approaches for simulating skin diseases into synthetic fingerprints were proposed. Method based on learning from existing images was implemented. As a sample disease psoriasis was chosen. Psoriasis is very frequent disease and also it has various effects on fingerprints.

Six different levels of severity were simulated. All of them were discussed with dermatologist and verified using three different quality measurement methods (VeriFinger's comparison score, NFIQ, and FiQiVi's quality metric). All damages have their median scores lower than the respective scores of the reference images. The best of the damage was extreme psoriasis damage (psor5), which has its average median scores only 38 % of the reference scores.

Acknowledgements

This research has been realized under the support of the following grants: The Ministry of Education, Youth and Sports of the Czech Republic from the National Programme of Sustainability (NPU II) project "*IT4Innovations excellence in science - LQ1602*" and "*Secure and Reliable Computer Systems*" – internal Brno University of Technology project FIT-S-17-4014 (CZ).

References

[Ba17] Barotová Š.: Detector of Skin Diseases by Fingerprint Technology. Bachelor's thesis FIT BUT, 2017, p. 50.

[Bř18] Březinová E.: Outer Hand Physiology and Diseases. Hand-based Biometrics: Methods and Technologies, IET, 2018, p. 26. ISBN 978-1-78561-224-4.

[DK19] Drahanský, M., Kanich, O.: Influence of skin diseases on fingerprints, Biometrics under Biomedical Considerations, Springer, 2019, p. 40, ISBN 978-981-13-1144-4.

[HKD18] Heidari M., Kanich O., Drahanský M.: Processing of Fingerprints Influenced by Skin Diseases. Hand-based Biometrics: Methods and Technologies, IET, 2018, p. 34. ISBN 978-1-78561-224-4.

[Ka18] Kanich O.: Research in Fingerprint Damage Simulations. Doctoral thesis FIT BUT, 2018, p. 148.

[Ke03] Kerkhof van de P.C.M.: Textbook of Psoriasis. Blackwell Publishing Ltd., 2003, p. 348. ISBN 1-4051-0717-0.

[Ko18] Košťák D.: Generation of Skin Disease Effects into Synthetic Fingerprints from Anguli Generator. Bachelor's thesis FIT BUT, 2018, p. 44.

[Ne18] NEUROtechnology: MegaMatcher 10.0, VeriFinger 10.0, VeriLook 10.0, VeriEye 10.0 and VeriSpeak 10.0 SDK – Developer's Guide. Version: 10.0.0.0., 2018, p. 2521.

[Or18] Oravec T.: Methodology of Fingerprint Image Quality Measurement. Master's thesis FIT BUT, 2018, p. 55.

[TWW04] Tabassi E., Wilson C.L., Watson C.I.: Fingerprint Image Quality. NISTIR 7151, National Institute of Standards and Technology, 2004, p. 72.