Generation of Skin Diseases into Synthetic Fingerprints

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Abstract

People suffering from skin diseases on their fingers have often problems with fingerprint biometric recognition. Therefore, it is necessary to train the recognition algorithms using databases of fingerprints acquired from such affected patients. However, such databases are hard to obtain. Therefore, we propose an algorithm of synthetic fingerprints modification, so that they appear as fingerprints affected by selected skin diseases. Two most common diseases have been chosen - warts and atopic dermatitis.

The proposed solution has been tested using NEUROtechnology VeriFinger and NIST NFIQ 2. The experimental results confirmed that the proposed solution modifies synthetic fingerprints in such a way that the recognition score of VeriFinger drops significantly and several NFIQ 2 quality features report a decrease in quality of the fingerprints.

Keywords: Synthetic Fingerprint, SFinGe, Skin Disease, Wart, Atopic Dermatitis.

1. INTRODUCTION

Fingerprint recognition is one of the most often used biometric technologies all over the world. Nowadays, users find it even on their mobile phones. It has been designed so that everyone can use it. However, a problem rises in case of people with some kind of skin disease, disallowing them to use fingerprint scanning technology in order to authenticate themselves.

Skin diseases represent an important issue in fingerprint recognition. Unfortunately, this problem is often not taken into consideration when designing such a device. Although precise numbers are hard to calculate, it is estimated that 20–25% of people suffer from some kind of skin disease [1]. With such a large number of potential users of fingerprint technology, scanning technologies should be ready to deal with certain effects that the diseases have on the fingerprint ridge structure.

This requirement leads to a larger demand on testing of recognition algorithms. However, large databases of fingerprints are required in order to perform such tests. It is also a very time-consuming task, as many people need to participate in order to acquire enough samples. In order to overcome these problems, a database of synthetic fingerprints can be used. With already existing tools, a large quantity of synthetic fingerprints can be generated in a short time. However, fingerprint images produced by synthetic fingerprint generating tools are often too perfect to be used for any meaningful testing of existing algorithms.

Therefore, we aim to alter the generated synthetic fingerprints, so that they appear as fingerprints of people suffering from various selected skin diseases. Using a database of altered fingerprint images, existing algorithms might be better prepared for users that suffer from such diseases.

The rest of the paper is organized as follows: The following section 2 introduces synthetic fingerprint generation methods. Selected diseases are described and fingerprint images analysed in section 3. In section 4, a method of fingerprint-affecting disease simulation is proposed and the results are presented. Section 5 deals with evaluation and verification of changes implemented into synthetic fingerprint and finally section 6 concludes the results achieved.

2. SYNTHETIC FINGERPRINT

With the ever-growing progress of fingerprint recognition systems adoption in many different areas, methodical and accurate performance evaluations of fingerprint recognition algorithms are needed. The evaluation is usually based on their recognition accuracy on test data. The evaluation process consists of three main steps [2]:

1. fingerprint images acquisition,
2. features extraction and matching in order to generate match scores,
3. match scores analysis in order to compute error rates.

Due to very small error rates to be estimated, a reliable evaluation method requires large databases of fingerprints. However, collection of a large database of fingerprints is [3]:

1. expensive in terms of money,
2. time-consuming,
3. problematic due to privacy legislation that applies to biometric features.

Synthetic fingerprint database has been used for example at a performance evaluation event *FVC2006 [4] (Fingerprint Verification Competition 2006)* along with three other databases containing real fingerprints. [5]

In order to overcome the difficult and time-consuming process of fingerprint collection, synthetic fingerprint generators can be used to produce large databases at very low cost in terms of money and time. For our solution, we have chosen a well-established synthetic fingerprint generator SFinGe[1].

2.1 SFinGe

One of the first approaches to realistic synthetic fingerprint image generation has been introduced by R. Cappelli from the University of Bologna in 2004 [3]. The generated synthetic fingerprints emulate real images acquired with on-line sensors such as capacitive or optical ones.

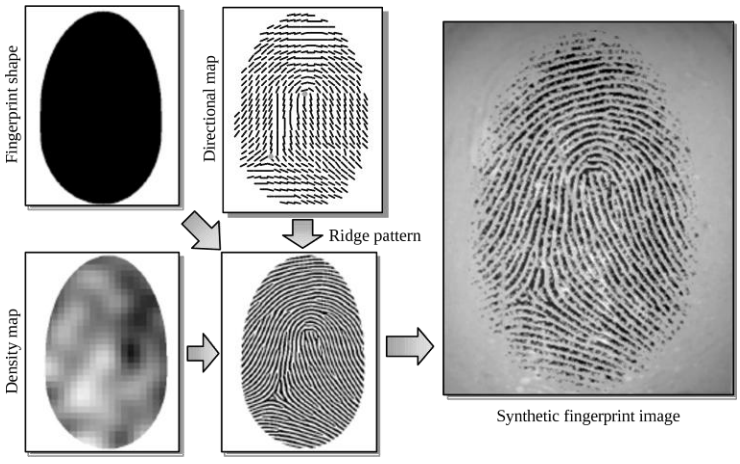

FIGURE 1: Basic steps of SFinGe method [3].

[1] http://biolab.csr.unibo.it/sfinge.html

The basic steps to create a synthetic fingerprint image are [3]: generate a fingerprint shape, a directional map and density map separately and combine the three features afterwards. The process of fingerprint generation process can be seen in figure 1. SFinGe method uses a master-fingerprint in order to derive several synthetic images of the same fingerprint.

SFinGe method is a mature synthetic fingerprint algorithm with a large variety of settings that can be modified. It produces high-quality images of realistic fingerprints. Authors provide two versions of the software tool, a free version limited to generating only one fingerprint at a time, and a full version capable of generating whole databases of hundreds of fingerprints.

3. DISEASE-AFFECTED FINGERPRINTS

Although it is well-known that fingerprints do not change in time, images of the same captured finger can vary a lot over a period of time due to many factors. These include injuries and bruises, peeling of the skin on the finger, current dryness of the skin, and also developing a skin disease affecting person's skin on fingers. [6]

Skin diseases represent an important factor of fingerprint acquirement process. However, it is often left out of consideration. The fact that this subject is ignored is supported by missing research in this area of fingerprint biometrics. Only two recent academic works conducted by Drahansky et al. [1] and Lee et al. [7] explore the effects of skin diseases on the fingerprint acquisition process. The work of Lee et al. concentrates on patients with hand dermatitis while the work of Drahansky et al. considers several various diseases and at the same time presents a way of enhancing the disease-affected fingerprint image to improve the success rate of enrolment and matching.

The following subsections deal with two selected most common skin diseases affecting fingers — *warts* and *atopic dermatitis*. First, the disease is described briefly and then an analysis of fingerprints affected by the disease is conducted.

3.1 Warts

Warts are caused by human papillomavirus (HPV) which belongs to a group of papovaviruses. There are more than a hundred of types of HPV and gene sequences of HPVs throughout the world are similar. Most of them cause specific types of warts and favour certain anatomic locations, such as plantar warts, common warts, genital warts, and so on. [8]

Primarily, our work focuses on *common warts* which are the most-spread variant of warts (affecting approximately 10% of the population [9]). They usually cause frustration to the patient. Social activities can be affected, lesions can be uncomfortable or bleed, and treatment is often painful and frustratingly ineffective [10].

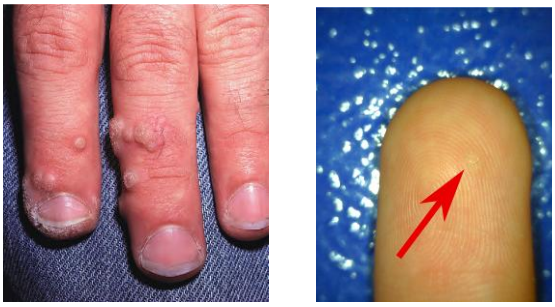

FIGURE 2: Common warts on hands and fingers [8].

Common warts are usually located on the hands, favouring the fingers and palms (see figure 2). Fissuring may lead to bleeding and tenderness. Lesions range in size from pinpoint to more than 1 cm, most averaging about 5 mm. They grow in size for weeks to months and are usually present as elevated, rounded papules with a rough, grayish surface. In some instances, a single wart (mother wart) appears and grows slowly for a long time, and then suddenly many new warts

erupt. On the surface of the wart, tiny black dots may be visible, representing thrombosed, dilated capillaries. Warts do not have fingerprint folds, as opposed to calluses, in which these lines are accentuated. [8]

3.2 Warts-affected Fingerprint Analysis

Let us now compare three different fingerprint images affected by warts (figure 3) that have been captured using a single sensor, Sagem MSO 300.

Fig. 3a shows a fingerprint with clean ridge structure except for the part where the wart is located. The wart is located near the right border of the image and on the image it is represented by a white circle-shaped object with several black dots irregularly spread over its surface. When the wart is relatively small, usually it contains little or no black dots at all.

In Fig. 3b, a single large wart is located near the core of the whorl. Black dots on top represent the hard and scaly skin of the wart. The wart is irregularly shaped and its border is well-defined. The ridge structure around the wart is mildly deformed and the ridges are compressed. However, except for the close surroundings of the wart, the ridge structure of the fingerprint is unaffected.

Fig. 3c shows a fingerprint that was affected by warts in a large area of its surface. There are at least three large white oval-like objects with irregular borders near each other. The warts affect the ridge structure near their edges similarly as the wart described previously.

FIGURE 3 (a,b,c): Different fingerprints affected by warts acquired by Sagem MSO 300.

From the available subset of STRaDe[2] research group fingerprint database, it has been found that the size of warts on fingers varies from very small ones to ones as large as half of the hypothetical radius of the fingerprint. The location of warts on fingerprint is random and often a single wart often produces other so-called satellite warts in its close surroundings.

3.3 Atopic Dermatitis

Atopic dermatitis (AD) [8] is a chronic, inflammatory skin disease that is characterized by pruritus and a chronic course of exacerbations and remissions. The prevalence of AD increased dramatically in the last half of the twentieth century, becoming a severe health problem in many countries. Rates of AD are around 15–20% worldwide with up to 20% of children affected by the disease [11].

The skin, in general, is dry and somewhat erythematous. Lichenification and prurigo-like papules are common. Papular lesions tend to be dry, slightly elevated, and flat-topped. They are nearly always excoriated and often coalesce to form plaques. [8]

The hands, including the wrists, are frequently involved in adults, and hand dermatitis is a common problem for adults with a history of AD. Hand eczema (figure 4) is the most common occupational skin condition, accounting for more than 80% of all occupational dermatitis. [8]

[2] http://strade-fs.fit.vutbr.cz/cms/en/

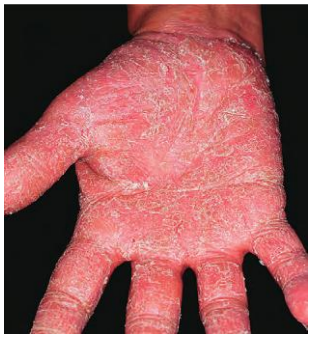

FIGURE 4: Hand eczema [8].

3.4 Atopic Dermatitis-affected Fingerprint Analysis

Let us now analyse three different fingerprint images affected by atopic dermatitis (see figure 5) that were captured using Sagem MSO 300 sensor.

The first figure 5a shows clearly wide and long white lines running throughout the whole fingerprint. The lines are mostly horizontally oriented. The finger is dry and ridge structure is in some areas of the fingerprint image less visible. On the other hand, other parts of the fingerprint show unusually dark areas with a damaged ridge structure.

Figure 5b is similar in the structure of the abnormal white lines to the previously described one. The lines run predominantly in horizontal direction with their length as large as the width of the fingerprint. Other thinner and shorter white lines can be seen in both, horizontal and vertical directions. The ridge structure is clearer than on the previous fingerprint image, however the patches are present as well.

Fingerprint on figure 5c contains many large white-only patches with no ridge structure whatsoever. In the centre of the image, there is a wide line running from the bottom-left corner through the centre of the fingerprint to the upper-right corner of the image. Other thinner lines can be seen in the left half of the fingerprint. As the ridge structure is mostly strongly damaged, this fingerprint image can hardly be used in an authentication system.

FIGURE 5 (a,b,c): A set of fingerprints affected by atopic eczema acquired by Sagem MSO 300.

To sum up, the two types of damage by atopic dermatitis are abnormal white lines and light and dark patches. According to Lee et al., the patches represent dystrophy of the skin and the median percentage of the surface area of dystrophy in their study was 22.80% [7].

The abnormal white lines usually run in horizontal or vertical direction and their length ranges from very short up to lines running throughout the whole fingerprint. According to the study of Lee et al., the median number of white lines per fingerprint was 12 and short horizontal lines prevailed (with occurrence in 73.0%), followed by short vertical lines (56.5%), long horizontal lines (52.5%), and long vertical lines (18.0%) [7].

4. FINGERPRINT DISEASE GENERATOR

In the following subsections 4.1 and 4.2, a design of methods for synthetic fingerprint modification is described in detail for each of the selected diseases. Finally, resulting fingerprint images are presented in subsection 4.3.

4.1 Warts-affected Fingerprint Generation

Based on the analysis of existing fingerprints affected with warts, design of a method for generating similar synthetic fingerprint images is proposed in this section. The algorithm consists of the following steps:

1. localise the fingerprint area on the image;
2. determine the wart size and locate its centre point in the fingerprint;
3. draw the wart into an image buffer:
    (a) create an empty image buffer;
    (b) generate a number of small circles around the centre point of the wart;
    (c) draw the generated circles into the buffer;
    (d) draw dark dots inside the wart;
    (e) determine the final colour of each wart pixel;
    (f) blur the wart in the buffer.
4. draw the wart from the image buffer into the fingerprint image;
5. generate possible secondary warts.

In order to generate warts into the synthetic fingerprint image, the fingerprint has to be localised in the input image first. This is done in step 1. First, an adaptive thresholding is applied in order to clearly separate the fingerprint structure from background. Then the image is blurred so that the fingerprint ridges connect and contours can be localised in the image. The contour of the largest area is then selected as the fingerprint contour (see figure 6). This contour then defines the border of the fingerprint.

FIGURE 6: Fingerprint area localisation (**a)** original fingerprint, **b)** blurring applied, **c)** fingerprint contour).

In step 2, a centre of the new wart is localised. The point coordinates are randomly generated and are used only if they comply with the requirements (location inside of the fingerprint, minimal distance from the fingerprint border). Also in this step, the size of the generated wart is randomly determined within boundaries set.

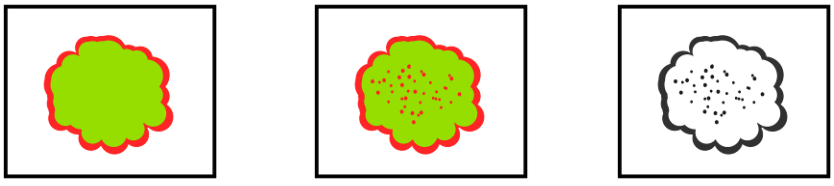

FIGURE 7: Wart drawing (**a)** wart drawn in distinctive colours, **b)** dots added, **c)** drawing in final colours).

Each new wart is first drawn into its own image buffer as not to interfere with the rest of the fingerprint. This is done in step 3 (see figure 7). First, an empty buffer of a size large enough for the new wart to fit in is created (step 3a). In the following step 3b, a number of small circles of varying radius is generated with their centres being distributed with exponentially large distance from the wart centre point. In the next step 3c, the previously generated circles are drawn into the buffer in distinctive colour (e.g. red or green) with their border drawn in a different distinctive colour (figure 7a). The final drawing step is step 3d in which the dots with randomly generated coordinates are drawn onto the warts surface. The dots are drawn with the same colour as the border of the small circles in the previous step (figure 7b).

FIGURE 8 (a,b): Wart drawing (steps 4 and 5).

With the wart shape drawn in the buffer, the algorithm proceeds with step 3e where the final colour of each pixel of the wart is determined (figure 7c). Depending on if the pixel is drawn by colour for border or the colour of the inside of the wart, the colour of the neighbouring pixels in the original fingerprint image is acquired (in this case dark pixels for border and light ones for the inside of the wart). The final pixel colour is then determined by one of the two following methods. First method picks random neighbouring pixel and copies its colour. The second method computes the mean colour of all the neighbouring pixels and then the mean colour is computed and applied to the pixel. Afterwards the buffer image is blurred slightly in step 3f in order to better fit into the original fingerprint image.

Finally, in step 4 the buffer is drawn into the original fingerprint image taking in consideration the transparency of the pixels in the buffer and blending them into the original image appropriately (figure 8a).

Eventually, secondary warts are drawn into the fingerprint if required in step 5 following the same steps of the algorithm as for the main wart (figure 8b). The only difference is an added requirement not to overdraw already existing warts in the image.

4.2 Atopic Dermatitis-affected Fingerprint Generation

Based on the analysis of existing fingerprints affected with atopic eczema, design of a method for generating similarly damaged synthetic fingerprint images is proposed in this section. The algorithm consists of the following steps:

1. localise the fingerprint area on the image;
2. create an empty image buffer;
3. draw eczema patches into the buffer:
    (a) determine the centre and size of the patch;
    (b) draw the patch of determined type (light, dark).
4. determine the final colour of each pixel of the patches;
5. blur the patches in image buffer;
6. draw eczema white lines into the buffer:
    (a) determine the starting point, direction, and length of the line;
    (b) generate line points in given direction and length;
    (c) interpolate the generated line points;

(d) draw the lines in determined thickness.
7. blur the lines in image buffer;
8. draw the buffer into the fingerprint image.

Step 1 of the algorithm is identical to the first step of the algorithm for generating warts. The result of this step is a contour of the fingerprint on the input image. Knowing precisely where the fingerprint is located in the image is necessary in order to draw onto the fingerprint area only and not outside of it.

In step 2, a new image buffer is created. The size of the buffer is the same as the size of the input image. The patches and white lines shall be drawn into the buffer separately as not to interfere with the original image.

First, the light and dark patches are drawn into the buffer in step 3. The number of patches is generated randomly within set boundary values. Afterwards the type (light, dark), size, and a centre point for each patch is determined in step 3a. If the centre point lies within the fingerprint boundaries, the algorithm proceeds to drawing the patch into the buffer. This is step 3b (see figure 9a). In this step, pixels in distance generated with exponential distribution from the centre point are drawn into the buffer in a distinctive colour (e.g. red or blue). It is randomly chosen if the pixels of the patch will later be in light colour or dark one.

When all the patches are drawn into the buffer in a distinctive colour, the final colour of each pixel is determined in step 4 (see figure 9b). First, the neighbouring pixels of each pixel in patch are collected from the input image. Then, based upon the selected algorithm, the final pixel's colour is either one of a randomly chosen neighbouring pixel or mean of all its neighbour's colours. After this, the patches in buffer are blurred in step 5 (see figure 9c).

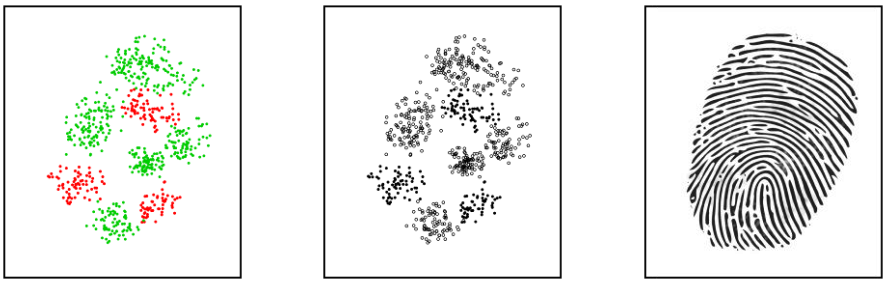

FIGURE 9 (a,b,c): Eczema patches drawing (steps 3, 4, and 5).

The second significant part of the algorithm takes place in step 6 where white lines are drawn into the buffer. Each part of the process is described in the following paragraphs.

In step 6a, parameters of each line are determined. The length of the line is determined within set boundary values and the line direction (either vertical or horizontal) is set. The starting point for line generation is found using random coordinates generation. The starting point must be sufficiently far from all other starting points of all other lines of the same type.

Line points are generated in step 6b. Beginning with the starting point, other leading points are generated based on the length of the line, the direction of the line, and a random generated angle within a pre-defined range (see figure 10a).

To make the lines look more realistic, in step 6c, the line leading points count is doubled and spline interpolation of the first order is applied. This makes the line appear less edgy and smooths it (see figure 10b).

Finally, each line is drawn into the buffer in step 6d (see figure 10c). The thickness of the line is set and the line is drawn in several steps starting with the whole length drawn in the smallest

thickness. Then the first and last leading points are removed and the line is drawn over with a higher thickness. This process repeats until the final set thickness is reached. This ensures that the line's width decreases towards line ends.

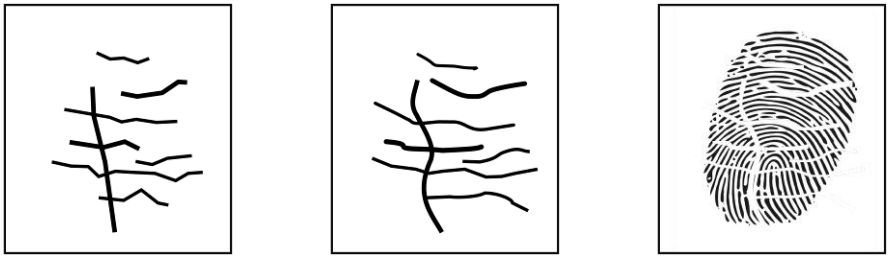

FIGURE 10 (a,b,c): Eczema lines drawing (into buffer) (steps 6b, 6c, and 6d).

In the last two steps, the buffer is once again blurred in step 7 and then in the following step 8, the buffer is drawn into the original fingerprint image taking in consideration the transparency of the pixels in the buffer and blending them into the original image appropriately.

4.3 Results

In this subsection, the resulting fingerprint images are presented. Figure 11 represents a selected set of fingerprint images to show the product of warts simulation. Subfigure 11a represents original synthetic fingerprint and next to it, on subfigure 11b, there is the same image with disease marks implemented in the *Fingerprint disease simulator*.

FIGURE 11: Results of fingerprint warts simulation (a) synthetic fingerprint, b) simulation result).

Similarly, the following figure 12 represents a selected set of fingerprint images to show the product of atopic eczema simulation. Subfigure 12a represents the original synthetic fingerprint while the same image with disease marks implemented in the *Fingerprint disease simulator* can be seen on subfigure 12b.

FIGURE 12: Results of fingerprint atopic eczema simulation (a) synthetic fingerprint, b) simulation result).

5. EXPERIMENTAL RESULTS

In order to evaluate the output of the *Fingerprint disease simulator*, the resulting damaged fingerprints must undergo verification against unmodified synthetic fingerprint images and their quality has to be measured. Thirteen sets, each containing 250 fingerprint images were generated with various parameters for evaluation. A detailed description of the datasets can be found in section 5.1.

Two methods of evaluation were selected. *VeriFinger*[12] by NEUROtechnology was used for the fingerprint verification. The output is a matching score of a damaged fingerprint expressed in a relation to a matching score of the original fingerprint that has been verified against itself. The results for both warts datasets and eczema datasets can be found in section 5.2.

NFIQ 2.0[13] fingerprint quality assessment tool was used to determine the quality of the damaged fingerprints compared to the quality of unmodified synthetic fingerprints. The output is a score based on several quality features computed from the fingerprint image. The results for the warts and eczema datasets are presented in section 5.3 in detail.

5.1 Description of Datasets

For the purpose of verification and quality assessment of the synthetic fingerprints with disease marks generated by the *Fingerprint disease simulator*, a total number of thirteen datasets were generated, each containing 250 unique fingerprint images affected by warts or atopic eczema. Each dataset was created with different set of parameters of the algorithm so that it can be evaluated which parameters affect the quality of the fingerprint the most.

The parameters of warts datasets are presented in table 1. Four datasets of warts-affected fingerprints were created in total. Warts dataset 1 and 2 are generated with warts size set to 5–10% of hypothetical radius of the fingerprint, while the size for dataset 3 and 4 is set to 10–15%. The maximum number of secondary warts *(Max. SW cnt)* is two for datasets 2 and 4. In case of datasets 1 and 3, they were disabled completely.

Dataset	Wart size [%]	Max. SW cnt
Warts 1	5–10	0
Warts 2	5–10	2
Warts 3	10–15	0
Warts 4	10–15	2

TABLE 1: Warts datasets parameters.

The number of eczema datasets generated for verification and quality assessment is nine and the parameters for each dataset can be found in table 2. The parameters include range of horizontal white lines count *(HL cnt)*, vertical lines count *(VL cnt)*, line length represented by percentage of hypothetical fingerprint radius *(L. length)*, line width *(L. width)*, patches count *(P. cnt)* and their size in percent relative to hypothetical fingerprint radius *(P. size)*.

Datasets 1–4 combine various line types and their length, while eczema datasets 5 and 6 add different line thickness. Datasets 7 and 8 contain different amount of patches with no lines and the last dataset 9 combines the vertical and horizontal lines with patches together.

Dataset	HL cnt	VL cnt	L. length [%]	L. width	P. cnt	P. size [%]
Eczema 1	4–12	0	50–100	8	0	0
Eczema 2	4–12	0	100–200	8	0	0
Eczema 3	0	2–6	50–100	8	0	0
Eczema 4	0	2–6	100–200	8	0	0

Eczema 5	4–12	2–6	50–200	8	0	0
Eczema 6	4–12	2–6	50–200	5	0	0
Eczema 7	0	0	0	0	2–10	20–80
Eczema 8	0	0	0	0	10–20	20–80
Eczema 9	4–12	2–6	50–200	8	4–20	20–80

TABLE 2: Eczema datasets parameters.

5.2 NEUROtechnology VeriFinger

For verification of generated disease-affected fingerprint, *VeriFinger*, a fingerprint identification tool by NEUROtechnology, was used.

The tool allows the user to enrol fingerprints into a database and verify or identify fingerprints against the existing database templates. During the process, a matching score is printed out. This score was used to evaluate the degree of the damage generated by the *Fingerprint disease simulator* into the synthetic fingerprint.

The methodology of the verification process is as follows:

1. enrol the original unmodified synthetic fingerprints into the database;
2. verify the same unmodified synthetic fingerprints and save their scores (this constitutes a baseline score — 100% score);
3. for each fingerprint from a given testing set, verify the damaged fingerprint against the original unmodified one and record the matching score;
4. evaluate the percent value of the recorded matching score — the normalized median value of the matching score;
5. calculate the median value for each set.

5.2.1 Warts

The results of warts-affected fingerprint verification are presented in table 3. The table contains the median of the set matching score and its normalized value. Graphical representation of the result values can be found on figure 13.

Dataset	**Original**	**Warts 1**	**Warts 2**	**Warts 3**	**Warts 4**
Median	1116.50	1037.50	1029.00	944.50	918.00
Norm. median [%]	100.00	93.47	92.74	85.80	83.42

TABLE 3: VeriFinger score: warts datasets.

From the data in table 3 it is clear that presence of warts in a fingerprint negatively affects the value of the fingerprint matching score. The *Warts 1* and *Warts 2* datasets are generated with only relatively small warts in size, while the other two datasets, *Warts 3* and *Warts 4* contain noticeably larger warts. Because of this, the score dropped by almost 10% when warts were relatively small (size parameters set to 5–10%) and by about 15% for larger warts (size parameter set to 10–15%).

Also the presence of secondary warts in datasets *Warts 2* and *Warts 4* decreases the final score considerably (by 0.73% in case of *Warts 1* compared to *Warts 2*; and by 2.38% for *Warts 3* and *Warts 4* datasets).

The most probable reason for this is that the wart in a fingerprint creates new minutiae while covering those present before the disease has been generated into the fingerprint. This fact results in lower matching score as some ridge structures cannot be properly matched by the algorithm any more.

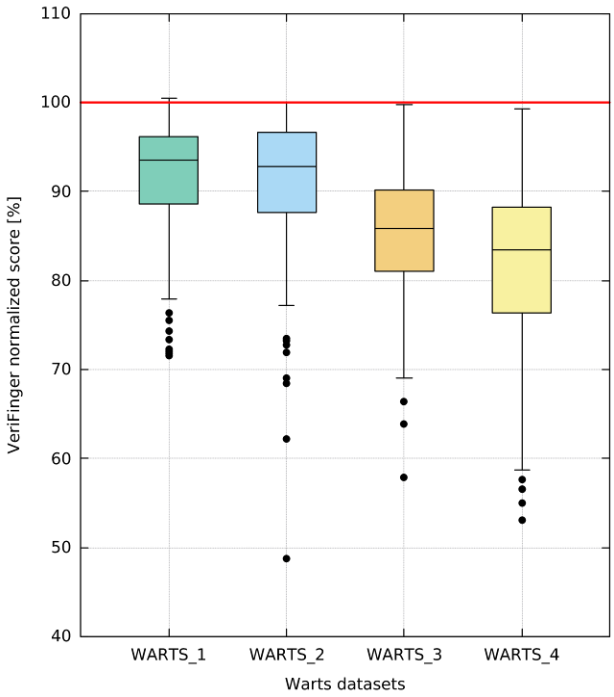

FIGURE 13: VeriFinger score: warts datasets.

5.2.2 Atopic Eczema

The results of atopic eczema-affected fingerprint verification are presented in table 4 containing the median of the set matching score as well as its normalized value. Graphical representation of the results can be found on figure 14.

Dataset	Original	Ecz. 1	Ecz. 2	Ecz. 3	Ecz. 4
Median	1116.50	836.50	841.50	855.50	857.50
Norm. median [%]	100.00	76.11	75.94	77.15	77.80

Dataset	Ecz. 5	Ecz. 6	Ecz. 7	Ecz. 8	Ecz. 9
Median	809.00	869.50	842.00	761.50	706.00
Norm. median [%]	73.79	78.33	76.25	68.20	64.30

TABLE 4: VeriFinger score: eczema datasets.

Judging from the data acquired, when comparing datasets *Eczema 1* and *Eczema 2* with datasets *Eczema 3* and *Eczema 4*, it can be said that the type of eczema lines in the fingerprint has only a little effect on the matching score (approximately 24% decrease for horizontal lines versus circa 23% decrease). The damage caused by the horizontal and vertical lines is principally the same. The white lines disrupt the flow of ridges and thus create new false minutiae in places of line crossing.

The length of the lines has a negligible effect on the final matching score. The difference of medians of datasets *Eczema 1* and *Eczema 2* is only 0.17% and in case of datasets *Eczema 3* and *Eczema 4*, the difference is 0.65%.

The small difference might be caused by the fact that a significant part of the line can be generated outside of the fingerprint. The reason for this is that while the starting point of the line is

generated to be inside of the fingerprint, the direction of the generated line is decided randomly. Therefore if the starting point is located near the fingerprint border and the direction is determined to point out of the fingerprint, the generated line might be in fact shorter than expected.

Examining the influence of line thickness on the matching score by comparing datasets *Eczema 5* and *Eczema 6* shows that thicker lines have a greater damaging effect on the fingerprint. The median of matching score for lines of maximal thickness 8 is only 73.79%, while the median of score for lines of maximal thickness 5 is 78.33%. This effect can be explained by the fact that thinner ridge disruptions might be repaired by the matching algorithm, while thicker lines discontinue the ridges more effectively.

Comparing the damage of each type of eczema marks (white lines versus patches), the one causing the greatest damage to the fingerprint are patches. Their effect is most significant when a large amount of patches is generated into the fingerprint. This demonstrates the comparison of dataset *Eczema 7* (2–10 patches per fingerprint) with median of matching score 76.25% versus dataset *Eczema 8* (10–20 patches per fingerprint) with median of matching score 68.20%. The patches in fingerprint make the ridge structure effectively less clear and bring more noise into it. This makes the minutiae recognition process for the matching algorithm harder to do, thus lowering the matching score.

The most effective damaging results are brought by both types of damage (white lines and patches) combined. As represented by dataset *Eczema 9*, the median of matching score declined to 64.30%.

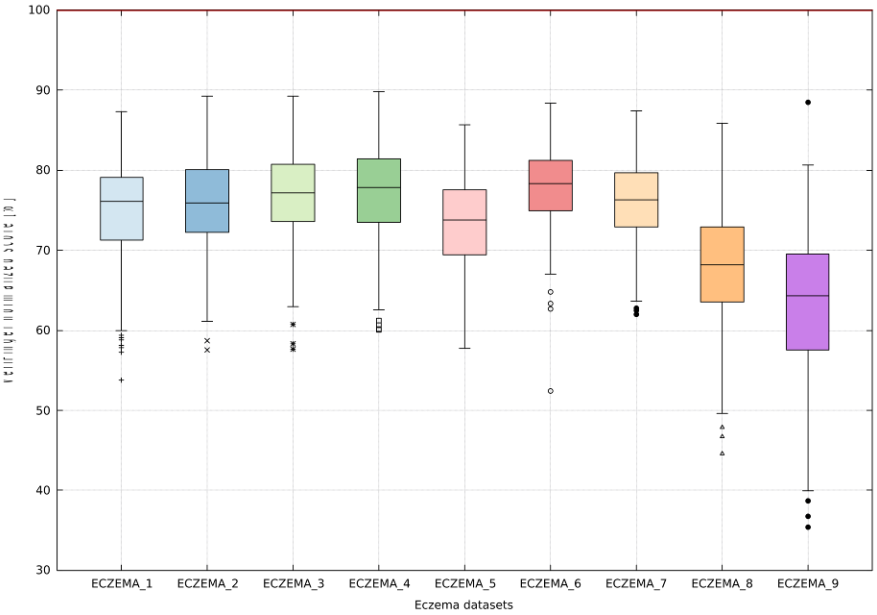

FIGURE 14: VeriFinger score: eczema datasets.

5.3 NIST NFIQ 2.0

The second method of verification of damaged synthetic fingerprints by the *Fingerprint disease simulator* was done with the help of *NFIQ 2.0* fingerprint quality assessment tool released by NIST (National Institute of Standards and Technology).

In order to assess the quality of a fingerprint, NFIQ 2.0 computes a set of quality features from the input image, and uses them to predict the fingerprint image quality. The output of the algorithm is a score value in range of [0–100], where 0 represents an image of no utility and 100 is the highest utility value. The NFIQ 2.0 algorithm bases its score computation on fourteen selected quality features which together constitute the final score for a given input image.

The base score was established for each fingerprint by evaluating the quality of the unmodified original synthetic fingerprint image. Then for each damaged fingerprint, its score was evaluated. A median of scores for each dataset was found and expressed in percent in relation to the base score median.

5.3.1 Warts

The results of warts-affected fingerprint quality assessment can be seen in table 5. The table contains the median of a set quality score and its normalized value. Graphical representation of the result values can be found on figure 15.

Dataset	Original	Warts 1	Warts 2	Warts 3	Warts 4
Median	64.00	66.00	66.00	67.00	67.00
Norm. median [%]	100.00	101.92	101.92	104.20	104.20

TABLE 5: NFIQ2 score: warts datasets.

As data in table 5 shows, the NFIQ2 score actually increased for all testing datasets of warts-affected fingerprints when compared to the unmodified original synthetic fingerprint dataset.

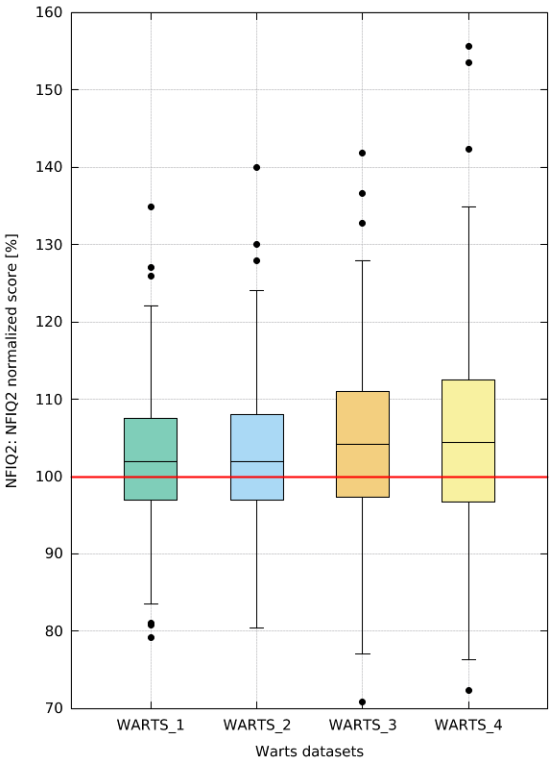

FIGURE 15: NFIQ2 score: warts datasets.

In order to explain this, the NFIQ2 score calculation has to be taken into account. The value of the score is based on fourteen various quality features computed from the input fingerprint image. Because the decision logic of the application is based on trained random forest learning, not all quality features have the same weight. Detailed information on the weight of each quality feature can be found in the NFIQ 2.0 documentation[3] (page 29).

[3] http://biometrics.nist.gov/cs_links/quality/NFIQ_2/nfiq2_report.pdf

Therefore, it can be assumed that the quality features affected by changes implemented by the *Fingerprint disease simulator* do not have weights large enough to influence the final NFIQ2 score. In fact, as in this case, some other quality features might be enhanced by the changes so that the final score rises above the score of the control set.

Detailed examination of several individual quality feature results can be found in section 5.4.

5.3.2 Atopic Eczema

Quality assessment results of fingerprints affected by atopic eczema can be found in table 6. The table contains the median of a set quality score as well as its normalized value. Graphical representation of the result values can be found on figure 16.

Dataset	Original	Ecz. 1	Ecz. 2	Ecz. 3	Ecz. 4
Median	64.00	65.00	64.00	63.00	64.00
Norm. median [%]	100.00	101.71	100.00	100.00	100.00

Dataset	Ecz. 5	Ecz. 6	Ecz. 7	Ecz. 8	Ecz. 9
Median	66.00	64.00	65.00	68.00	68.00
Norm. median [%]	102.03	100.00	101.79	104.67	104.67

TABLE 6: NFIQ2 score: eczema datasets.

Also in the case of eczema datasets, the NFIQ2 quality score is equal or higher than the score of the control dataset. The reasons were described in the previous section and are also the same in this case.

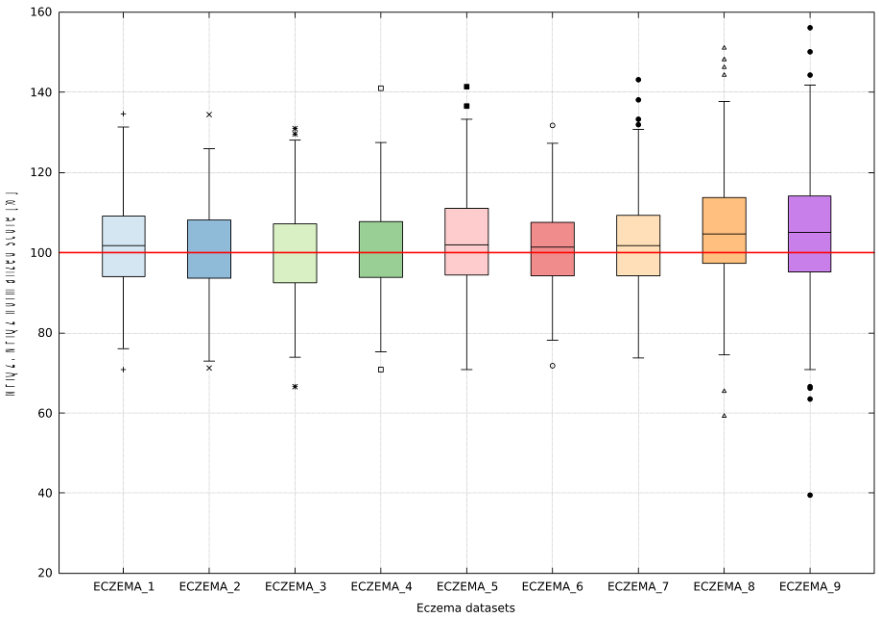

FIGURE 16: NFIQ2 score: eczema datasets.

5.4 NIST NFIQ 2.0: Selected Quality Features

In order to explain the higher value of NFIQ2 score for all datasets of damaged fingerprints, while the exact opposite was expected, the NFIQ2 score computation method has to be studied. As it was stated above, the score value is calculated from fourteen unique quality features with various weights. Thus, in order to verify that the changes made by the *Fingerprint disease simulator* bring significant damage marks into the fingerprint, let us investigate the scores of several selected

quality features evaluated by the NFIQ 2.0 algorithm. Only quality features that expressed a noticeable change in the score were selected into the set of examined quality features. Others stayed rather constant when compared to control dataset of unmodified synthetic fingerprints, therefore there is no need to study them further.

The NFIQ 2.0 employs a customized version of *FingerJet FX OSE minutia extractor*[4] for determining the amount of minutiae detected in the whole image *(Minutiae cnt)* and an arithmetic mean of all minutiae quality values. Two different methods for computing the quality of the minutiae are used.

The first method calculates the quality using an arithmetic mean of pixel values in the input image *(MU M. Quality)*. The second method of minutiae quality assessment computes the quality as the *Orientation Certainty Level* of blocks of pixels centred at the minutia location *(OCL M. Quality)*.

The other quality features presented are *ROI Relative Orientation Map Coherence Sum (OM Coherence)* which represents the average coherence values over all image blocks in the fingerprint ROI.

The last of the studied quality features is the *Ridge Valley Uniformity (Uniform Image)* feature. It measures the consistency of the ridge and valley widths. For a finger image with clear ridge and valley separation it is expected that the ratio remains rather constant and thus the standard deviation of the ratios is used as an indication of the fingerprint quality.

5.4.1 Warts

The evaluation results of selected quality features of the NFIQ 2.0 algorithm for warts-affected fingerprints datasets are presented in table 7.

Dataset	Original	Warts 1	Warts 2	Warts 3	Warts 4
Minutiae cnt	36	38	37	43	45
MU M. Quality [%]	85.00	83.00	84.00	75.00	71.00
OCL M. Quality [%]	77.00	71.00	69.00	60.00	55.00
OM Coherence [%]	75.00	74.00	74.00	73.00	72.00
Uniform Image [%]	53.72	53.49	53.42	53.23	53.06

TABLE 7: NFIQ2: selected quality features: warts datasets.

From the summarized results it can be deduced that changes brought by the *Fingerprint disease simulator* generating warts, increase the number of detected minutiae in a fingerprint. This means that the newly detected minutiae must be false ones. Increasing the size of warts also increases the number of new false minutiae.

The quality of minutiae measured by both methods previously described also decreases with increasing size of warts generated. Original quality score values of 85% and 77% go down as low as to 0.71% and 0.55% for dataset *Warts 4* containing generated warts of a large size (10–15%) and secondary warts generating enabled.

As far as *OM Coherence* and *Uniformity of Image* quality features are concerned, their score values differ insignificantly from the original control dataset.

To sum up, for warts-affected fingerprints, new false minutiae are detected by the minutiae extractor and their quality is significantly lower than the quality of minutiae found on the original fingerprint image. Other score values change only negligibly.

[4] https://github.com/FingerJetFXOSE/FingerJetFXOSE

5.4.2 Atopic Eczema

The results of selected quality features evaluation of the NFIQ 2.0 algorithm for datasets containing fingerprints affected by atopic eczema are presented in table 8.

Dataset	Original	Ecz. 1	Ecz. 2	Ecz. 3	Ecz. 4
Minutiae CNT	36	36	36	36	35
MU M. Quality [%]	85.00	79.00	79.00	82.00	80.00
OCL M. Quality [%]	77.00	75.00	76.00	76.00	76.00
OM Coherence [%]	75.00	75.00	75.00	75.00	75.00
Uniform Image [%]	53.72	49.50	49.66	49.69	49.87

Dataset	Ecz. 5	Ecz. 6	Ecz. 7	Ecz. 8	Ecz. 9
Minutiae CNT	36	36	36	37	40
MU M. Quality [%]	78.00	82.00	79.00	71.00	68.00
OCL M. Quality [%]	72.00	76.00	69.00	46.00	43.00
OM Coherence [%]	74.00	75.00	73.00	67.00	67.00
Uniform Image [%]	49.00	49.61	43.20	36.70	37.58

TABLE 8: NFIQ2: selected quality features: eczema datasets.

Judging from the summary of results presented the minutiae count does not change significantly for eczema-affected fingerprints. The only exception for this rule is the last dataset *Eczema 9* which contains fingerprints damaged by all types of available eczema marks. In comparison to other datasets which keep the same number of detected minutiae as the control dataset, the median value of minutiae detected in dataset *Eczema 9* is 40.

The only considerable quality change of the minutiae of fingerprints affected by eczema can be observed in *Eczema 8* (71% and 46% versus 85% and 77% for the control dataset) and *Eczema 9* datasets (68% and 43% versus 85% and 77% for the control dataset). Other datasets do not show such a significant change in quality. The most probable reason for this is that the last two datasets contain a large number of eczema patches generated into the fingerprints. This decreases the quality of minutiae measured by both of the methods of fingerprint minutiae quality assessment.

As far as *ROI Relative Orientation Map Coherence Sum (OM Coherence)* quality feature is concerned, the only significant change can be seen in *Eczema 8* and *Eczema 9* datasets (the score of both is 67%). The score of control dataset is 75% and the other dataset scores range between 73% and 75%. Again, this is caused by a large number of eczema patches present in fingerprints contained in *Eczema 8* and *Eczema 9* datasets.

For the *Uniformity of Image* quality feature, the score of patches-containing datasets decreases noticeably while datasets containing fingerprints with eczema lines record only a small decrease in score value (approximately 4% decrease). Even a small number of patches brings the score value down to 43.20% for dataset *Eczema 7*. Larger decrease of the score value can be seen in *Eczema 8* and *Eczema 9* datasets (36.70% and 37.58% versus the control dataset value of 53.72%).

All in all, except for the minutiae count, all other quality features are negatively affected by a large number of eczema patches present in a fingerprint image. On the other hand, eczema lines do not have such a significant effect on the score value of selected quality features.

6. CONCLUSIONS

The aim of our work was to design an algorithm for modifying a synthetic fingerprint image in a way similar to the way a real disease would do. In order for the goal to be fulfilled, a number of subjects concerning fingerprint biometry had to be studied.

From the STRaDe database of disease-affected fingerprints, two most common diseases were selected: *warts* and *atopic eczema*. For each of the disease, further study was carried out. Based on the samples available from the database, an analysis of selected fingerprint images was conducted and disease-specific features described. Based on the analysis, design of a method for the specific disease generation was proposed. The resulting outputs of the proposed solution were presented.

The simulation results are datasets of synthetic fingerprint images with varying disease-specific marks on them. In case of warts, typical circle-shaped objects are generated into the fingerprint with black dots inside. Simulation output images for eczema are represented by various white lines and colour patches generated into the synthetic fingerprint image.

Conducted experiments were described in chapter 5. In order to verify the damaging effect caused to the synthetic fingerprints by simulating diseases marks to them, thirteen datasets (four warts and nine eczema datasets) each containing 250 fingerprint images were generated in total. Each dataset was created using various parameters so that it could be later examined which parameters affect the fingerprint recognition process in what way. Two methods were used to verify the fingerprints and assess their quality: *VeriFinger* by NEUROtechnology and *NFIQ 2.0* algorithm by NIST.

When evaluated with the VeriFinger algorithm, warts datasets showed decrease in the matching score depending on the generated warts size. The score for the dataset of warts with the size parameter set to 10–15% and secondary warts generation enabled went as low as 83.42% of the control dataset score.

Even more significant was the decrease of matching score for datasets of eczema-affected fingerprints. For datasets with fingerprints containing white eczema lines only, the score dropped by approximately 23–24% to 76–77% of the control dataset score. It was also found that more damaging are thicker lines (score of 78.33% for thickness 5 versus 73.79% for line thickness 8). By far, the most damaging effect on the fingerprint ridge structure have eczema patches. The matching score of datasets generated with the patches enabled dropped to 68.20% of the control group score. When patches and eczema lines were combined, the matching score recorded went down to only 64.30%.

As far as the quality assessment is concerned, the final score of the NFIQ 2.0 quality assessment tool did not reflect changes made by the *Fingerprint disease simulator* as expected. The reason for this is that the final score is computed based on fourteen various quality features, each of them having various weights in the algorithm. Therefore, several specific quality features have been selected instead and their results are discussed further.

For warts datasets, there has been an increase in minutiae count compared to the control dataset (up to 45 versus 36 detected minutiae per fingerprint) meaning that the disease marks simulated by the *Fingerprint disease simulator* create new false minutiae in the fingerprint. Along with that, the quality of minutiae decreased significantly, measured by two different methods (by up to 14 percent points and by up to 22 percent points). Other quality features changed only slightly.

Eczema datasets showed almost no new false minutiae creation (except for the last dataset combining the eczema patches and white lines, where the minutiae count rose up to 40 compared to 36 minutiae per fingerprint for the control dataset). However, the quality of the minutiae dropped significantly, mainly in datasets with large number of generated patches. The quality dropped by up to 9 percent points by one measuring and by up to 32 percent points measured by the second method. Also the other two quality features (*ROI Relative Orientation*

Map Coherence Sum and *Uniformity of Image*) dropped significantly for the datasets with large number of generated patches (from 75% down to 67% for the *OM Coherence* and from 53.72% down to 37.58% for the *Uniformity of Image*).

All in all, the changes to the synthetic fingerprints made by the *Fingerprint disease generator* are well-measurable. In case of warts, the main aspect influencing the damage extent is the size of the generated warts and the amount of them. As far as atopic eczema is concerned, the main influencing aspect is the count of eczema patches, while eczema white lines have a minor effect.

The impact of this research is that recognition algorithms will no longer perform significantly worse for patients suffering from various skin diseases compared to unimpaired users thanks to the introduction of our method. The method proposes a way of generating large databases of synthetic fingerprints with marks of skin diseases such as warts or atopic eczema. These databases can then be used to train fingerprint recognition algorithms to perform better for users with such skin diseases.

7. FUTURE RESEARCH

For this research, two most common skin diseases have been chosen to simulate: warts and atopic eczema. The *Fingerprint disease simulator* was designed so that it can be extended with new modules simulating other fingerprint diseases as well. For a good understanding of the studied diseases, further ongoing cooperation with dermatologists will be required.

Another way of utilising the research outcomes is in designing and testing of a tool for automatic recognition of skin disease from fingerprint image.

All in all, incorporating the proposed method, matching algorithms could profit from the virtually unlimited amount of fingerprints generated in order to adapt themselves and improve the fingerprint recognition of fingerprints with various diseases.

8. ACKNOWLEDGEMENTS

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