GENERATING SYNTHETIC IRIS IMAGES FOR TESTING BIOMETRIC SYSTEMS

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Abstract: Usage of biometric methods of person identification has recently become quite popular. Many developers are working on new biometric systems which have to be tested using biometric data. This work proposes the ways of generating synthetic biometric data designed for testing of iris based biometric systems. Two iris texture generation methods are presented here – one is based on Perlin noise, the other on the image quilting algorithm. Also a hybrid approach combining both methods is presented. The results of tests were also presented to demonstrate the utility of images generated using these methods in testing biometric systems and the consistency of the results obtained with the results for real images.

Keywords: iris, biometrics

1. Introduction

In recent years interest in biometric authentication systems has increased. This applies not only to professional applications, such as banking or security, but also access to a notebook or smartphone. One of the highly effective features is the image of the iris of the eye. It is characterized by high sample uniqueness as well as safety of use.

To assess the effectiveness of a biometric system, it is necessary to test it on a large data set. Probably the best test will be to use it in real conditions, on real data. However, the testing procedure can be significantly accelerated by using artificial data generated by the algorithms. In this way, we eliminate the tedious data acquisition procedure from the process. Alternatively, thanks to artificial data, we can multiply the size of our data set at a low cost. This can be especially important in the case of features whose acquisition is expensive or complicated.

This work presents a proposal to solve this problem. Two ways to generate artificial iris images for biometric purposes are presented here – the first one uses Perlin

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noise [9], the second one combines fragments of natural images into synthetic samples. A hybrid method combining both solutions was also presented. The paper also presents the results of experimental tests to assess the suitability of the generated samples in the study of biometric systems.

2. Iris in biometric systems

The iris is a ring visible through the cornea that gives the eye color. Each iris has a dark back layer, the amount of pigment on the front and upper parts determines its color [10]. The main purpose of the iris is to adjust the pupil size to the current lighting. The iris has muscles that allow it to narrow and extend the pupil in response to the state of the body (eg fear, relaxation, sleep) or light intensity.

The iris pattern is usually rich in numerous bands and spots, which makes it a useful biometric feature. It has over 200 characteristic points, over four times more than the fingerprint [3]. It is recognized that details decorating the iris ring arise randomly during the development of the eye in the fetus. There are not yet two people with identical characteristics of the iris, even in the case of identical twins, the patterns of these details differ.

In early childhood, the amount of pigment and also the color of the iris may change. However, the later appearance of it remains in a relatively permanent form until death, after which it succumbs to self-destruction in a matter of seconds. It can therefore be concluded that the iris of the eye is a permanent biometric feature.

Systems based on the iris are also characterized by high acceptability. The measurement requires some cooperation from the tested person, however its duration is small and the process is relatively simple.

Additional procedures in biometric systems allow their effective protection against fraud attempts. For example, the technique that illuminates the examined eye can determine whether it responds correctly to changes in light intensity. In the case of false irises, the size of the pupil will not change. These systems are therefore characterized by high security.

2.1 Daugman's biometric system

John Daugman developed [3] the first fully functional and commercially used system that uses the iris of the eye for identification purposes, which has become the standard in its field. Daugman's patent described methods of sample acquisition, segmentation of the iris ring, normalization of data received, coding of a feature vector, and a method of comparing two processed biometric samples.

The first step is to take a biometric sample – a digital image of the eye from the examined person. Daugman suggested using the near-infrared spectrum to minimize the discomfort of the person being photographed. It is crucial to choose the appropriate wavelength and focus, allowing for accurate registration of the structure of the iris.

From the eye image received in the previous step, the part corresponding to the iris should be find. For this purpose, an approach known from face detection systems is used. The shape sought is described by a set of parameters defining its pattern. To describe a circle corresponding to the edge of the iris, three parameters are enough: x and y coordinates of its center, and its radius r. Daugman proposed a search of the space of values of these parameters using the integral-differential operator [4].

The outer edge of the iris is usually partially covered by the eyelids, the inner edge may be disturbed by light reflecting off the surface of the eye. In addition, the characteristics of both edges are affected by glasses. The method of active contours designed by Daugman [4] tolerates this type of disturbance.

The next step following the segmentation is to describe the characteristics of the iris in a way that allows comparison with other samples. Not all images have the same size – the distance of the eye from the camera affects the size of the iris in the picture, besides, lighting can cause the pupil to shrink or dilate. Daugman solved this problem by mapping the area of the iris obtained during segmentation to the normalized coordinate system – the iris ring is rolled into a rectangular ribbon, where the radius coordinates are on the vertical axis and the angular position on the horizontal axis.

Direct comparison of two images is largely susceptible to errors due to differences in lighting during their acquisition. To extract the clean structure of the iris, Daugman used a weave operation using two-dimensional Gabor filters. In the final vector of features, each pixel corresponds to two coded values depending on the real and imaginary value returned by the applied Gabor filter. Negative numbers are remembered as zero, positive as 1. In this way, the IrisCode is created – a 2048-bit code containing the characteristic features of the iris of the eye.

To compare two different iris codes, Daugman used the Hamming distance [6]. It allows measuring the part on which the compared strings differ.

2.2 Synthesis of iris data

Daugman's 1993 work is considered a breakthrough in the field of iris biometrics. Since its publication, interest in the techniques of classifying this biometric feature has increased. Methods of generating artificial data have also begun to appear.

In the work of Jiali Cui et al. from 2004 [2] a method was proposed to create a database of artificial eye images for testing biometric systems. It is based on the principal components analysis allowing the creation of iris images of the same class by appropriate selection of the feature vectors coefficients. In addition, it uses the super-resolution method to improve the quality of generated images. According to the calculations included in the work, this technician allows to create over 280 000 data classes under the described conditions. Conducted in 10 000 study classes using the Daugman system using the threshold obtained in the teaching process, they returned zero FAR and FRR error values.

In the work of Samir Shah and Arun Ross from 2006 [11], a technique for generating synthetic iris using the feature agglomeration was proposed. The image is created by synthesizing the iris background based on the Markov model and the real eye sample. Then, elements such as stripes or spots are added depending on the characteristics of said sample. In order to verify the results of the work, the authors carried out tests with the Daugman system comparing the differences in the codes within the three sets: filled with artificial and real images, and a set containing both types of images. Distributions of result data were similar for each case.

The paper of Jinyu Zuo et al. from 2007 [12] describes an approach that puts more emphasis on modeling the anatomy of the entire eye. At the beginning of the proposed method, continuous fibers are generated in a three-dimensional cylindrical space. Then, the layer imitating the eyeball is applied to the fiber projected onto the two-dimensional space. Finally, eyelids and randomly generated lashes are synthesized. In order to better simulate real samples, this technique takes into account effects that distort the generated images – noise, revolutions, light reflections and blur. The generated images were analyzed at the visual level and taking into account the vectors of iris features. They were also verified using the Daugman algorithm implementation to compare the real result distributions and the generated iris.

Despite the passage of about ten years from the first publication on the subject, the problem of generating synthetic eye images is still valid, as can be found, for example, in the work of Cardoso et al. from 2013 [1]. In addition to the precise generation of single layers of iris fibers, the developed synthesis method deeply addresses many aspects that allow realistic rendering of the human eye. In their work, the authors have taken into account the pupil distortion model, the sclera and the blood vessels placed in it, the light reflection properties of both the eye and the eyelids, and the ability to reproduce the reflected image of the surroundings on the surface of the eye. Intra-class diversity has been tested taking into account, inter alia, the sharpness of the image, the degree of closed eyelids, the distance and position of the head relative to the camera, lighting, pupil size or distortions caused by the glasses.

Qualitative tests comparing the generated base to existing real eye image databases were successfully carried out using the classic Daugman method based on images obtained using infrared light and a method using the visible spectrum.

3. Generating iris images for testing biometric system

As a part of the research, two algorithms for generating artificial iris images and a way of composing them with real eye photographs have been developed.

The most commonly used images in near infrared systems were used as the reference image. The goal was to create unique images of the iris rings. The remaining elements of the eyeball and surrounding face elements are not taken into account during the extraction process of features, therefore there is no need to ensure their unique appearance. The images generated for the needs of the work were created using the University of Tehran iris image depository UTIRIS[1] [8]. Fig. 1 shows an example sample from the aforementioned database.

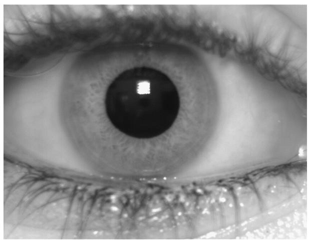


Fig. 1. Sample image from the UTIRIS iris data base

The process of eye image generation is as follows. The first step is to generate the texture of the iris ring. The following subsections describe two different approaches to this issue. The first proposes to use the method of noise generation created by Ken Perlin, the second assumes the use of existing iris samples to assemble a new image using the algorithm designed to generate textures developed by Efros and Freeman [5]. Regardless of the technique chosen, a rectangular image is generated (Fig. 2).

The iris strip obtained should then be rolled up to take the form of a ring. It is worth noting, however, that the circle of the inner edge of the iris does not have to be

[1] `https://utiris.wordpress.com/`

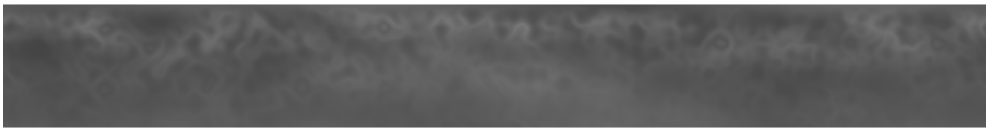


Fig. 2. Sample texture generated using Perlin noise

concentric with the circle of the outer edge, which is taken into account in this work. Figure 3 shows the texture image after the transformation.

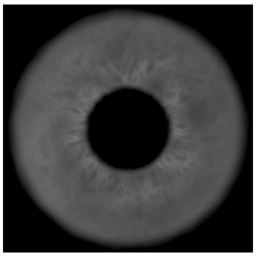
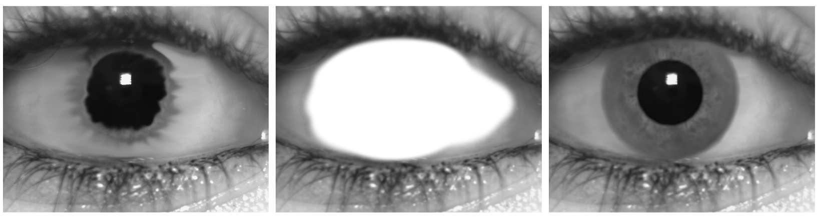


Fig. 3. Iris ring folded from the texture from Fig. 2

The last step is to combine the image so obtained with the real image of the eye. For this purpose, two manually created images are used as the bottom and top layer. The bottom layer contains the image of the iris-free eye, the image generated by the algorithm is applied, and then the image of the eyelid, which may partly obscure the pasted image of the iris, overlaps. These images were prepared manually using free, open-source raster graphics editor GIMP. The result of such composition is shown in Figure 4.



a b c

Fig. 4. Bottom layer (a), top layer (b), composite image (c)

To provide several biometric samples of the same person, five images of the eye were generated based on each iris strip. In order to simulate different images of the same eye, the generated images differ from each other in the size of the pupil and the slight angular deviation of the iris ring.

3.1 Generating iris images using Perlin noise

The first of the methods to generate an artificial iris image described in this work was created as a result of experimental attempts to synthesize Perlin noise samples. The essence of the method is to combine pseudorandom noise images of different frequencies into one that visually reproduces the characteristic irregularities that occur in the iris of the human eye.

At the beginning, using the Perlin algorithm [9], two images are generated with different frequencies (the frequency of the second is two times higher than of the first one), on the basis of which an averaged image is created (Figure 5).

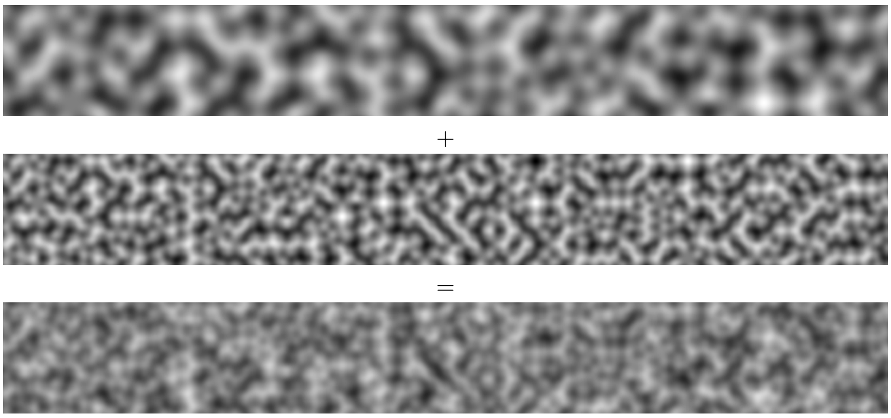


Fig. 5. The result of the averaging of two Perlin noise images with different frequencies

In the next stage, in order to obtain details that imitate the iris spots, the image palette is modified. As a result of a series of experiments involving the visual comparison of the effects of various functions, a formula enabling this operation was created:

$$f(x) = \begin{cases} 0.5 + 0.5 \cdot \sin(x \cdot 2\pi + \frac{\pi}{2}) & \text{if} \quad x \leq 0.25 \\ 0.5 + 0.5 \cdot \sin((x - 0.25) \cdot 2\pi) & \text{if} \quad 0.25 < x \leq 0.50 \\ 1 - \sin(x \cdot \pi - \frac{\pi}{2}) & \text{if} \quad x > 0.5 \end{cases} \tag{1}$$

Where the x value for black pixel is 0, and for white is 1. The result of the operation is shown in the Fig 6.

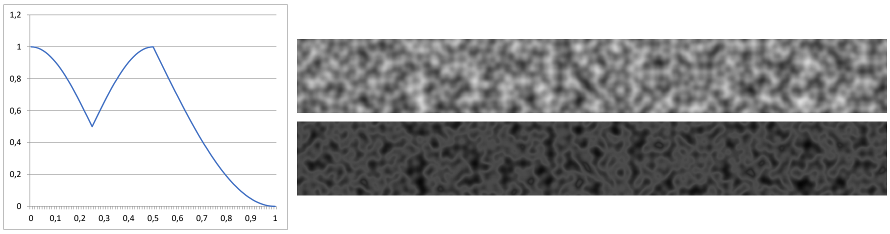


Fig. 6. Plot showing the palette function $f(x)$ and the noise image before and after modification

The next step is to reduce the detail level in the received image. For this purpose, another image is generated using Perlin noise (of frequency two times lower than the first of images from the step presented in Fig. 5). It serves as a detail map that adds uniform gray spots to the image being processed (Figure 7).

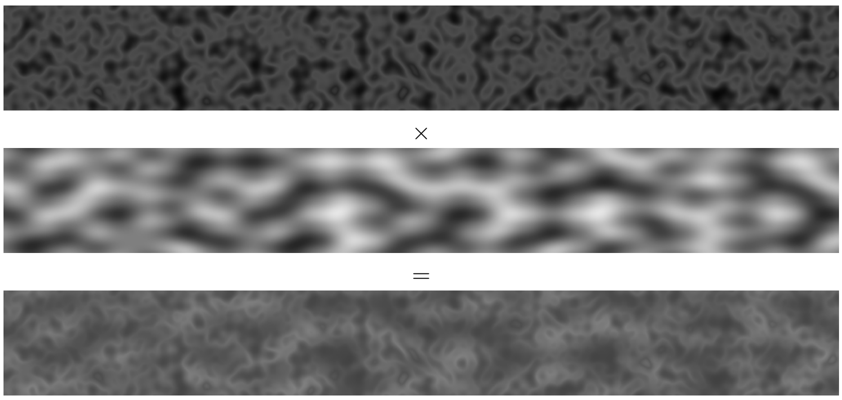


Fig. 7. Detail reduction operation

The operation shown in Figure 7 is defined by the formula:

$$y = (1 - m) \cdot x + 0.25 \tag{2}$$

Where: x is pixel value of the source image, m – pixel value of the mask. The image obtained in this way will be used in the inner part of the iris ring, where the intensity of the characteristic points is greater. For the outer part, another sample of Perlin noise is created, this time with a small frequency (four time smaller than in the previous step) and amplitude (five times lower). It is presented in Fig. 8.

Fig. 8. Image created on the basis of Perlin noise with low frequency and amplitude

The final stage of the algorithm is the combination of the inner and outer parts of the iris using the mask created specially for this purpose (Figure 9). Interpolation along the vertical axis was made using the sine function, irregular elements are the result of applying an additional layer of noise to an unnaturally smooth gradient.

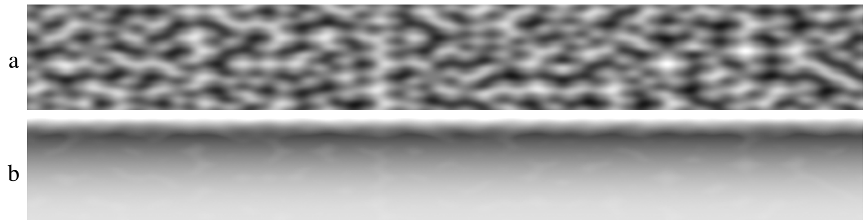


Fig. 9. Mask for combining the outer and inner texture of the iris (b) and Perlin noise used to create that mask (a)

Finally, after generating all the necessary elements, the final iris image can be created (Fig. 10). The operators used in this step are the same as in the previous ones.

3.2 Generating iris images using image quilting algorithm

The second method to generate the artificial iris image used in the work is based on the image quilting algorithm of Alexei A. Efros and Wiliam T. Freeman [5]. The following description presents the proposed method to use this technique when generating synthetic images of the iris.

Image quilting involves creating images from existing samples. Therefore, in order to generate the texture of the iris, a collection of source images is needed, on the basis of which new images will be created. In the research described in the work,

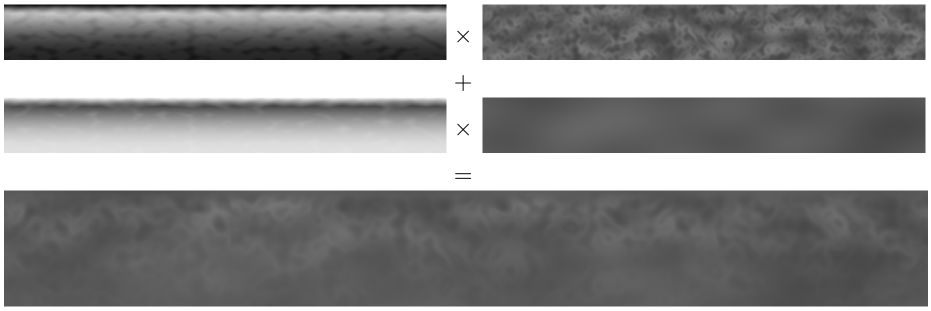


Fig. 10. Combining component images into the final iris texture

the UTIRIS database [8] was used. Out of 30 images of different classes, rectangular stripes representing iris (Figure 11) were obtained by unfolding the ring.

Fig. 11. Picture of the eye from the UTIRIS database with its iris after unfolding

From the unfolded iris strips, the fragments corresponding to the eyelids should be removed (Figure 12), and then the brightness of the images should be modified so that the average value of the pixel on each of them is equal. These steps were performed under human control to prevent errors of the automated system.

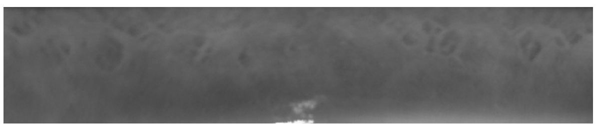


Fig. 12. Iris strip from Figure 11 after removing fragments containing the eyelids

Iris textures were made of forty-eight combined source fragments (in three rows, sixteen columns) with dimensions of 64×42 or 64×43 pixels plus an additional 10 pixels for each edge touching with another fragment (Figure 13.) Iris stripes with a resolution of 1024×128 pixels were obtained.

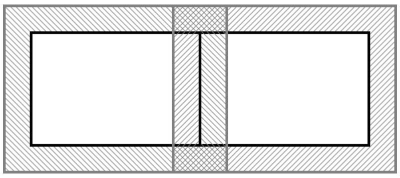


Fig. 13. A schematic diagram of the arrangement of two adjacent fragments – black indicates the inner, non-overlapping part, while the gray color – the edge overlapping the adjacent slices

The first step of the algorithm is to draw one of thirty previously prepared iris strips, from which a fragment of the appropriate size is randomly selected. The drawing takes place in the upper half of the iris strip so that the fragment contains the characteristics of the inner ring. The resulting fragment is placed in the upper left corner of the image.

For the remaining forty-seven elements, selecting one from thirty strips is repeated. This time, the drawn strip is searched in order to find a rectangle that best fits the image from the previous step. The decision is made on the basis of the sum of pixel differences in the contact area of the fragments. The smallest sum means that the fragment should blend well with the previously generated texture. The overlapping area is then marked with a path dividing it into two parts. The A* algorithm [7] is used to search for the shortest path, where the road graph is based on a matrix of pixels, and the weights of the points are equal to the square difference of the corresponding pixel values. The selected fragment is cut according to the calculated path and then applied to the resultant image. Fragments of subsequent lines must include two overlapping areas (overlapping the previous part of the line and the previous line). An exemplary image of the generated iris texture strip with marked connection lines is shown in Figure 14.

For the described case, in which the final image is the result of joining forty eight patches selected from thirty iris stripes, the number of possible combinations is 30^{47} multiplied by the number of possible random results of the first fragment (value of the order 10^{79}).

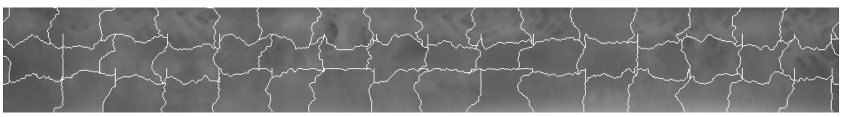


Fig. 14. Generated texture of the iris with marked joint lines

3.3 Image testing

The main issue addressed in this work is to generate artificial biometric data. It is difficult to assess the quality of the results obtained without first testing them using a biometric system. For this purpose, an application was created that allows to identify and verify the classes of generated images.

The quality indicator of generated images is their degree of uniqueness. In this case, a simplified version of the original Daugman algorithm, implemented in the developed application, will suffice. Simplification consists primarily in omitting the iris segmentation phase.

The implemented algorithm consists of stages of normalization and extraction of features. At the beginning, the iris ring from the loaded image is unfolded into rectangular strip. The next step is to use a convolution operation using Gabor filters. As a result, two matrices are created: real and imaginary. With the help of the coding proposed by Daugman, positive values are converted into ones and negative values are changed to zeros (Figure 15). The length of received codes depends on the resolution adopted during the normalization of the strips containing iris data.

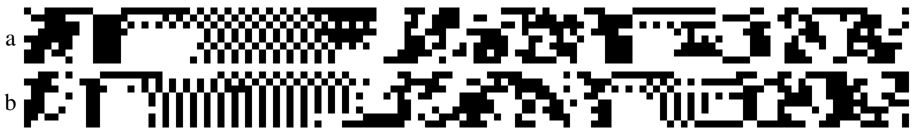


Fig. 15. Coded real (a) and imaginary (b) parts of the result

The process of loading and transforming images into binary codes is performed for all tested images. After receiving the set of codes grouped with classes, it is possible to start testing.

4. Experimental results

For the purpose of this research, a thousand iris classes were generated using each of three different methods:

- using Perlin noise (subsection 3.1),
- using the image quilting algorithm (subsection 3.2),
- a hybrid approach using image quilting, in which the source images are both the real iris images and those generated using Perlin noise.

For each of classes, five images of the same eye with different degrees of irises were generated. In addition, the images are characterized by a slight angular deviation, with each sample from one class was deviated in a different degree in relation to the others.

From among the generated images, three sets of 250, 500 and 1000 data classes were created (1250, 2500 and 5000 images respectively). All collections were tested in terms of both identification and verification using leave-one-out crossvalidation method.

The generated images were tested using the algorithm described in chapter 3.3. Performance metrics for a biometric data array of sizes 32×4, 32×8, 64×8 and 128×8 bits were compared.

4.1 Iris images generated using Perlin noise

The Ken Perlin's noise algorithm is characterized by high speed. Generator, created for this reaserch, managed to produce 1090 different iris classes in one hour (data for Intel Core i5-520M).

The results of verification tests (equal error rate values) are presented in Table 1. As one can see, the use of 64×8 bits matrix already provides virtually zero ERR value.

Table 1. Error of verification for Perlin images

Feature matrix	250 classes	500 classes	1000 classes
32×4	1%	0.8%	0.9%
32×8	0.06%	0.05%	0.05%
64×8	0%	0%	0%
128×8	0%	0%	0%

The results of identification tests are shown in Table 2. For each of the tested sets using the matrix 64×8 and 128×8, an accuracy of 100% was obtained.

4.2 Iris images generated using image quilting

The disadvantage of this algorithm is its computational complexity. The generator created for the needs of this work, managed to produce only 102 different iris classes in one hour (data for Intel Core i5-520M).

The results of verification are presented in Table 3. A 0% equal error rate values were obtained for matrices with sizes 128×8 bits.

Table 2. Results of identification for Perlin images

Feature matrix	250 classes	500 classes	1000 classes
32×4	99.6%	99.24%	99.1%
32×8	100%	99.96%	99.98%
64×8	100%	100%	100%
128×8	100%	100%	100%

Table 3. Error of verification for quilt images

Feature matrix	250 classes	500 classes	1000 classes
32×4	.3%	2.4%	2.4%
32×8	0.55%	0.57%	0.57%
64×8	0.01%	0.02%	0.02%
128×8	0%	0%	0%

The results of identification tests are presented in Table 4. As before, for each of the tested sets using the matrix 64×8 and 128×8, an accuracy of 100% was obtained.

Table 4. Results of identification for quilt images

Feature matrix	250 classes	500 classes	1000 classes
32×4	96.72%	94.96%	93.00%
32×8	99.76%	99.84%	99.78%
64×8	100%	100%	100
128×8	100%	100%	100%

4.3 Iris images generated using hybrid algorithm

Images are generated at the same speed as those described in previous subsection, because the hybrid technique uses an identical algorithm. Only the source elements from which the images are created are changed.

The generated images were tested analogously to the images described in previous subsections, the results are presented in Tables 5 and 6.

In the verification tests, for a features array of 128×8, the result of 0% equal error rate was obtained. The 64×8 and 128×8 matrices provide 100% correct identification for all three data sets.

Table 5. Error of verification for hybrid images

Feature matrix	250 classes	500 classes	1000 classes
32×4	1.5%	1.4%	1.4%
32×8	0.18%	0.2%	0.2%
64×8	0%	0.01%	0.01%
128×8	0%	0%	0%

Table 6. Results of identification for hybrid images

Feature matrix	250 classes	500 classes	1000 classes
32×4	99.20%	98.40%	97.56%
32×8	100%	100%	99.92%
64×8	100%	100%	100%
128×8	100%	100%	100%

4.4 Results comparison

It can be seen, that the best verification results have been obtained with images created with the algorithm that uses Perlin noise. Identification tests gave similar results. Except one case of a 32×8 matrix for a set of 500 classes, images based on Perlin noise showed the highest percentage of correctly identified samples.

Based on the obtained results, it can be concluded that the images generated using the Perlin noise technique are characterized by the highest degree of uniqueness. At the same time, it is the fastest method and allows to generate a large collection of images with unique biometric data classes.

It is worth noting that all tests carried out on matrices with sizes 128×8 bits (a total of 2048 bits) fell one hundred percent successfully. The size of the vectors tested by Daugman in 1993 [3] was just 2048 bits. The number of classes tested by him is 323 – more than three times smaller than in this work. It can therefore be assumed that synthetically generated irises are characterized by a sufficiently high diversity.

4.5 Comparison of generated images with the real ones

The strength of the authentication system is determined not only by the algorithms for processing attributes and classifications used, but also the correct calibration – that is, determining the thresholds for which the system rejects the person applying for access. For this purpose, training data is necessary. They can be real data or artificial data obtained using the methods described above.

To ensure that iris images generated by the developed methods are suitable for testing and calibrating biometric systems to a similar extent as real images, comparative studies were carried out. For this purpose, four sets of iris pictures were collected, 50 classes each. Three containing iris formed on the basis of each of the methods discussed and one consisting of real images from the UTIRIS iris database. Each of the sets was subjected to verification tests allowing to determine optimal thresholds and values of balanced errors using a data matrix with sizes of 32×4, 32×8, 64×8 and 128×8 bits. The results obtained are presented in Table 7.

Table 7. Thresholds (TH) and errors (ERR) received during verification tests

	32x4		32x8		64x8		128x8	
	TH	ERR	TH	ERR	TH	ERR	TH	ERR
Perlin's noise	0.9	0.5%	1.6–2	$\sim 0\%$	1.7–2.8	0%	2.2–3.1	0%
Image quilting	1.05	1.3%	2.1	0.1%	2.4–2.8	$\sim 0\%$	2.7–3.1	0%
Hybrid approach	0.95	0.6%	1.8–2.1	$\sim 0\%$	2–2.8	0%	2.5–3.1	0%
UTIRIS	1.15	13%	2.4	11.9%	3	4%	3.3	2%

The threshold values shown in the Table 7 indicate the maximum acceptable mean number of matrix column elements on which the bits do not match. For each of the sets tested with the same matrix sizes similar values of optimal thresholds were obtained. The data set based on the UTIRIS database is characterized by the highest values. The most close results for generated data are obtained by the image quilting technique. On the other hand, the images generated using Perlin noise are characterized by the threshold values most deviating from natural samples.

The obtained values of the equal error rate differ to a larger extent between sets of artificial and real images. For the smallest size matrix among the tested, they range from 0.5% to 1.3% in the case of artificial collections, while the real images get as much as 13%. For larger sizes, the error value drops to 2%, while for artificial images it approaches 0%.

The reason for such large discrepancies in the obtained values of the equal error rates can be a simplified iris segmentation model applied during the performed tests. While the images generated contained exact data about the position and size of the iris ring, in the case of photos from the UTIRIS database it was necessary to determine these data in advance. In the case of any errors, the iris strips may have become distorted at the standardization stage, negatively affecting later attempts to match the pattern. The threshold values determined on the basis of the research of each of the collections turned out to be similar. In this case, the generated images of iris seem to fulfill their role, which is to enable the initial calibration of biometric systems without the need to obtain real biometric data.

5. Conclusions

Research on images created by designed methods has demonstrated the utility of simple pseudorandom algorithms, such as Perlin noise, in the field of biometrics. The authors' work, unlike the approaches presented in section 2.2, is not based on realistic modeling the eye structure. It was proposed to use universal image processing methods to create images that imitate images of real irises. Despite the trivial solution, it allows to test biometric systems. In the case when a large number of classes is an important element of research, Perlin noise seems to be a good solution, because it allows to generate a large data set with a low calculation cost. This feature even allows to generate data on the fly, avoiding the need for storage.

Images synthesized using the method of image quilting, apart from uniqueness enabling creation of data sets, showed a visual similarity to real images. This raises the question of whether other commonly used methods for generating textures are also suitable for use in the field of eye biometrics testing. Probably these universal techniques can also be applied to other biometric features. The presented solution is the first approach of the authors to the topic of generating artificial biometric data, other possibilities will be investigated in the future.

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GENEROWANIE SYNTETYCZNYCH OBRAZÓW TĘCZÓWEK DLA CELÓW TESTOWANIA SYSTEMÓW BIOMETRYCZNYCH

Streszczenie Rośnie popularność stosowania metod biometrycznych w identyfikacji osób, wielu badaczy pracuje nad nowymi systemami, a wymaga to danych, na których można by je testować. W niniejszej pracy zaproponowano sposób generowania sztucznych danych biometrycznych dla potrzeb testowania systemów bazujących na biometrii tęczówki ludzkiego oka. Przedstawiono dwie metody – jedna bazuje na szumie Perlina, natomiast druga na algorytmie generowania tekstu image quilting. Przedstawiono również podejście hybrydowe, łączące obydwie metody. Zawarto również wyniki testów, mających pokazać użyteczność obrazów wygenerowanych przy pomocy zaproponowanych metod w opisywanym zastosowaniu. Pokazano również ich spójność i podobieństwo do prawdziwych danych.

Słowa kluczowe: tęczówka, biometria

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