

Secure Biometric Verification Station Based on Iris Recognition

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Abstract—This paper describes an application of the Zak-Gabor-based iris coding to build a secure biometric verification station (SBS), consisting of a professional iris capture camera, a processing unit with specially designed iris recognition and communication software, as well as a display (LCD). Specially designed protocol controls the access to the station and secures the communication between the station and the external world. Reliability of the Zak-Gabor-based coding, similarly to other wavelet-based methods, strongly depends on appropriate choice of the wavelets employed in image coding. This choice cannot be arbitrary and should be adequate to the employed iris image quality. Thus in this paper we propose an automatic iris feature selection mechanism employing, among others, the minimum redundancy, maximum relevance (mRMR) methodology as one, yet important, step to assess the optimal set of wavelets used in this iris recognition application. System reliability is assessed with approximately 1000 iris images collected by the station for 50 different eyes.

Keywords—*application of biometrics, feature selection, iris recognition, Zak-Gabor-based iris coding.*

1. Introduction

Iris recognition has recently emerged as one of the top biometric authentication methods due to its accuracy and outstanding identification efficacy. It is also commonly believed that the pattern of iris tissue is highly stable throughout the human life, although recent scientific notifications start to surprisingly suggest the opposite hypothesis. However, without a doubt, iris recognition became a mature technology supported by numerous implementations in places requiring reliable identity verification, and the most common applications concern border and physical control. This paper is conformable with this trend, as we apply the iris recognition as a key element of a secure verification station, being a server of biometric-based verification. The station is autonomous, i.e., it consists of image capture hardware, the processing unit with the operating system and the display for communication with verified subjects. The electronic communication with the station is secured by a protocol specially designed to the purpose of this application.

The iris recognition used in this work is based on original methodology employing Zak-Gabor transformation [1]. The optimal features selection procedure consists of two

stages: selecting the best iris features – in terms of an iris recognition efficiency – in the first stage, and selecting the optimal Zak-Gabor-based coding parameters based on the results of the first stage [2]. For reading fluency, the applied Zak-Gabor-based coding is briefly explained in Section 2, some remarks related to the iris template creation and matching are provided in Subsection 2.4, and an in-depth explanation of the feature selection mechanism is presented in Section 3.

Selection of coding parameters, i.e., the optimal wavelet families emphasizing the relevant individual iris features, is strictly dependent on the database, in particular on the quality of iris images used. The resulting parameters estimate an optimal, yet unknown, configuration of wavelet transformation adequate in the iris template creation. However, when applied to other image sets (not used at the estimation stage), these transformation parameters typically result in a lower accuracy than expected (in particular the genuine comparison results deteriorate, e.g., see p. 289 in [3]). It is thus reasonable to adapt – if possible – the coding parameters to the expected iris image quality by estimating the optimal features using the database collected in the assumed scenario, i.e., employing target equipment operated in a target (or precisely modeled) environment, and applying all possible procedures that are expected at the operational stage.

However, feature selection is a very demanding process, especially when rich datasets are to be applied and the feature space is significantly large. Therefore, achieving a global minimum of the recognition error cannot be often guaranteed within acceptable time (or cannot be achieved at all due to a huge number of calculations that make the search process infeasible), and we have to be satisfied by quasi-optimal solutions. Repeating this process prior to any application of our recognition methodology may be thus annoying. To make the iris feature selection an easy process, and further to select satisfying parameters of the Zak-Gabor-based coding, we have built a tool that performs this task automatically for provided dataset of iris images, Section 4.

To build a secure verification station we decided to use one of the existing iris capture cameras and our choice was mainly motivated by speed of capture and ease of use, due to high priority of practical aspects of the station. As we expected differences in quality of images captured by the

station and images used to build the original method, we finally applied the developed feature selection tool to adapt the coding and improve the accuracy. The achieved three-fold reduction of the EER justifies the need of adaptation for a new image quality. The station development is described in Section 5.

2. Zak-Gabor-Based Iris Recognition

This section briefly presents the Zak-Gabor-based iris coding [1], [2], developed earlier by the first author, and used in this work to build a tool for automatic iris features selection, which finally is applied in the developed secure station.

2.1. Iris Images and their Segmentation

Iris recognition starts from the acquisition of an iris image of sufficient quality. The raw image contains the iris but also its surroundings, and the iris is often disturbed by occlusions, thus it has to be processed prior to feature extraction, Fig. 1. Building a map classifying the image points into those representing the iris and lying outside the iris is called the segmentation. Although the feature extraction routines are directly responsible for delivering iris features, the segmentation process mostly influences a reliability of iris recognition, and most of current endeavors go towards development of robust iris segmentation methods.

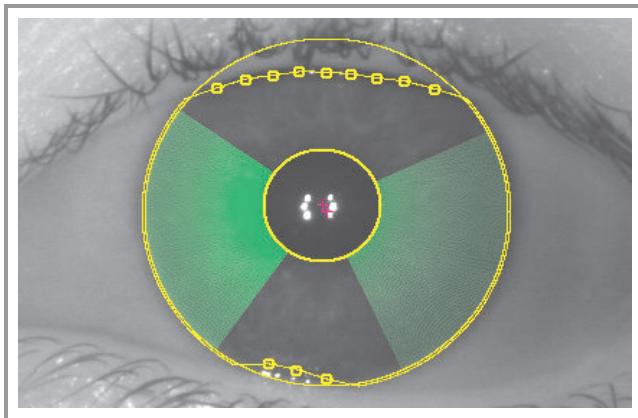


Fig. 1. Iris image captured by the station and the segmentation result. The two circles approximate inner and outer boundaries of the iris. Small empty circles point to the detected occlusions, and the broken line approximates them between detection points. Two sectors, automatically selected by the segmentation procedure, cover the iris portion used in feature extraction.

The segmentation method used in this work comprises of two main stages: localization of the inner and outer boundaries of the iris, and localization of any disruptions occluding the iris tissue. Neither the iris nor the pupil are circles, nevertheless, due to the simplicity and speed of algorithm implementations, it is a common practice to model the iris

boundaries by circular, non-concentric shapes. The method applied in this paper employs a modified Hough transform to detect circular shapes, and the coarse-to-fine analysis is applied to speed up the calculations, i.e., rough positions of the pupil and the iris are first determined in a low resolution, and higher resolutions are used to precise the final result.

Two determined circles representing inner and outer boundaries only roughly approximate the actual iris region, due to occlusions that typically exist in iris images. To detect local non-uniformity within the iris body, a set of angular directions is constructed, originating from the iris center in which the iris texture is analyzed. Among all the angular directions, a set of *reference directions* are singled out, which cover those sections that are known to be always free of occlusions, and they are used for calculation of the maximum allowed non-uniformity. Once the maximum allowed non-uniformity is set, the iris region is analyzed for each analysis direction and an occlusion is detected when the irregularity in a given direction exceeds the reference. This procedure constructs an occlusion map as a series of radii, each representing the distance between the iris center and the boundary of the occlusion (cf. small empty circles in Fig. 1).

Based on localized occlusions, the method sets two independent iris sectors, each of 90° in angular width, to be further used for features extraction. The choice of angular width was made at the stage of development of the Zak-Gabor-based method, and it was based on experiments with the iris enrollment images. Since users of the secure station are not forced to open their eyes in a particular way during capture, it is concluded that once the eyelid coverage is too high, the system may ask for the eye to be opened more widely to finally extract two such sectors with minimum effort by the user. As ISO recommends [4] to have at least 70% of iris body not obscured, the assumption that two iris sectors – constituting only 50% of the iris body – free from occlusions can be found, seems not to be very demanding.

Iris texture analysis may be qualified as a 2D pattern analysis task, yet it is often simplified to a set of 1D problems. The Zak-Gabor-based method maps two iris sectors into R one-dimensional P point functions. We further call these functions *stripes*, as they represent image intensity distributed along angular direction, and for each angle the resulting value is calculated within small radial neighborhood, resembling the division of each iris sector into $R/2$ stripes. These one-dimensional functions are further used in the Zak-Gabor-based method to extract iris features.

In order to ascertain whether the acquired image is of the required quality (in terms of focus and iris body availability), the Zak-Gabor-based method investigates two additional image attributes: focus factor and the iris body coverage by eyelids. These attributes are basis for separate ‘experts’ judging on the image quality, and giving a binary decision whether the image passed the test. It is assumed

that image quality (from the iris recognition perspective) is sufficient if both experts' answer is affirmative.

2.2. Zak-Gabor-Based Iris Features

The Zak-Gabor-based method characterizes a discrete-time signal in the joint time-frequency domain, describing its stationary energy distribution locally, thus finding the distribution of signal energy in local (possibly overlapping) time segments. As we deal with images, not time series, the 'time' variable is replaced by the 'position' variable in this work. The Zak-Gabor-based method performs this local analysis by a family of wavelets, each characterized by a quadruple: scale, frequency and radial/angular positions. Since it is difficult and not recommended to set an arbitrary scales, the natural extension of such position-frequency analysis is to allow the scale and to be adapted independently of the frequency coordinate. Thus directing these calculations toward the so called *wavelet packet* analysis. Following [2], we explain briefly the calculation principles of the Zak-Gabor coefficients, being a base for iris features used in this work.

Let g_s be a one-dimensional Gaussian function characterized by scale index s , sampled at points $0 \dots P-1$, namely

$$g_s(p) = e^{-\pi((p+\frac{1}{2})/2^s)^2} \quad (1)$$

where $s = 2, \dots, S$ and $S = 8$, and the factor of $\frac{1}{2}$ lets g_s to be symmetric over the sampling grid when P is even. The *Gabor elementary function* (GEF) [5] is defined as shifted and modulated version of g_s , namely

$$g_{mk;s}(p) = g_s(p - mK)e^{ikp2\pi/K}, \quad p = 0 \dots P-1. \quad (2)$$

Let M be the number of translations of g_s , and K be the number of frequency shifts, where m and k denote position and frequency shifts, respectively ($m = 0, \dots, M-1$, $k = 0, \dots, K-1$), and g_s is wrapped around the P -point domain. Zak-Gabor-based iris coding applies critical sampling and always takes $M = P/K$. Let f_ℓ be the intensity function defined on a stripe ℓ . The finite discrete Gabor transform of f_ℓ is defined as a set of complex-valued coefficients $a_{mk;s\ell}$ that satisfy the Gabor signal expansion relationship, namely

$$f_\ell(p) = \sum_{m=0}^{M-1} \sum_{k=0}^{K-1} a_{mk;s\ell} g_{mk;s}(p), \quad p = 0 \dots P-1 \quad (3)$$

and $K = 2^s$ is set in further analysis. Note that the number S of scales together with the stripe size P determine both M and K .

The set of $a_{mk;s\ell}$ coefficients is a base of iris features. Gaussian-shaped functions, used in the Zak-Gabor transform, are however not orthogonal (the inner product of any two of all functions is nonzero), therefore its coefficients cannot be determined in a simple way, and Zak's transform is applied for this purpose. The discrete finite Zak transform $\mathcal{Z}f_\ell(\rho, \phi; K, M)$ of a function f_ℓ sampled equidistantly at P points is defined as the one-dimensional

discrete Fourier transform of the sequence $f_\ell(\rho + jK)$, $j = 0, \dots, M-1$, namely [5]

$$\mathcal{Z}f_\ell(\rho, \phi; K, M) = \sum_{j=0}^{M-1} f_\ell(\rho + jK) e^{-ij\phi 2\pi/M} \quad (4)$$

where $\phi = 0, 1, \dots, M-1$, $\rho = 0, 1, \dots, K-1$ and $M = P/K$. Application of the discrete Zak transform (4) to both sides of (3) yields

$$\mathcal{Z}f_\ell(\rho, \phi; K, M) = \mathcal{F}a_{s\ell}(\rho, \phi; K, M) \mathcal{Z}g_s(\rho, \phi; K, M) \quad (5)$$

where $\mathcal{F}a_{s\ell}[\rho, \phi; K, M]$ denotes the discrete 2D Fourier transform of an array of $a_{s\ell}$, representing the coefficients determined for the iris stripe ℓ and scale s , and $\mathcal{Z}g_s[\rho, \phi; K, M]$ is the discrete Zak's transform of the Gaussian window g_s . The expansion coefficients $a_{mk;s\ell}$ can be thus recovered from the product form (5) and choosing K and M to be a power of 2 yields possibility of FFT application, thus making computation times proportional to those in the FFT. As this way of calculating the Gabor expansion coefficients is often called the Zak-Gabor transform [5] (instead of simply Gabor transform), we further call $a_{mk;s\ell}$ coefficients as the *Zak-Gabor coefficients*.

Zak-Gabor-based iris coding defines the signs of the real and imaginary parts of Zak-Gabor coefficients $a_{mk;s\ell}$ as iris feature set \mathbb{B} , namely

$$\mathbb{B} = \{ \text{sgn}(\Re(a_{mk;s\ell}), \text{sgn}(\Im(a_{mk;s\ell})) \} \quad (6)$$

where $m = 0, \dots, M-1$, $k = 0, \dots, K-1$, $\ell = 0, \dots, R-1$ and $s = 2, \dots, S$. Since the Fourier transform of real signals (e.g., iris stripes f_ℓ are real) consists of two parts being complex conjugates of each other, for each position m the coefficients with the frequency index $k > K/2$ are ignored. Since $M = P/K$, for each s there are $(N-1)P/2$ coefficients determined. Taking into account that this analysis is carried out for all iris stripes, and remembering that $R = 32$, $S = 8$ and $P = 512$, the total number of coefficients calculated for the iris image is $R(S-1)P/2 = 57,344$. Both real and imaginary parts are coded separately by one bit, hence $N = \#(\mathbb{B}) = 114,688$ features (bits) are achieved.

2.3. Iris Features Matching

The order of features (bits) is kept identical for all images and thus the matching requires only a XOR operation between two feature sets. The Hamming distance is applied (as it is typically done for binary feature vectors) to calculate the score ξ , namely

$$\xi = \frac{1}{N} \sum_{n=0}^{N-1} (b_n^{(1)} \text{ XOR } b_n^{(2)}) \quad (7)$$

where $b_n^{(i)}$ is the n -th bit of i -th sample. Factor $\frac{1}{N}$ makes $\xi \in \langle 0, 1 \rangle$.

2.4. Iris Template Creation and Verification

Iris templates used by the Zak-Gabor-based coding consist of iris code bits and positions of the individual sectors (calculated within the segmentation procedure) for which the iris features are determined. The sector positions are necessary to allow calculating the code at the same angular positions each time the images have to be matched. The implementation of the Zak-Gabor-based which is used in this work [6] may use any number of iris images (starting from just one) to create the iris template, however, capturing more than one image at the enrollment is recommended. In the latter case we may take advantage of the Zak-Gabor-based implementation that selects the best iris code among a number of those calculated for the enrollment images. Namely, if multiple images are available at the enrollment time, the template creation procedure first rotates all the images to the one representative which is the least rotated to all the remaining images. Next, for all images the iris sectors are determined and their average positions are taken. The consistency of the codes is checked by calculating the comparison scores between the analyzed code and the codes related to the remaining enrollment images, obtained for these new (averaged) sector positions. To finalize the template creation, all the comparison scores must fall below the acceptance threshold, which denotes that the enrollment images were of sufficient quality to deliver information about the iris texture. If any of the matching results exceeds the acceptance threshold, the procedure allows for a replacement of the defective image and calculations are partially repeated.

In contrary to the enrollment procedure, the verification should proceed quickly, in particular only single image is acquired. However, the absolute eyeball slope cannot be assessed accurately in one-eye capture system, as it was applied in the secure station, and no such information is linked to the template. Once an eye is rotated during capture relatively to the images employed in the enrollment process, corresponding features apply to different parts of the iris, thus making the features inadequate. Using a raw iris image at the verification stage, without correcting eye rotation may lead to false rejections. The implementation of the Zak-Gabor-based coding solves this problem by generating a series of iris templates at the enrollment stage and each of the generated template corresponds to one micro-rotation of the original iris (in both directions). The angles of these micro-rotations are not equidistantly placed in the angular axis, and were selected according to the sample distribution of observed rotations in this application. It produced a map of rotations, with greater number of elements near zero (small rotations are more probable) and less elements near the maximum rotations observed (as they are still probable to occur, yet less than the smallest ones). It slightly extended the enrollment procedure (as the Zak-Gabor-based features has to be calculated several times), yet the eyeball rotation compensation at the verification stage is done in the blink of the eye, as only a few (instead of one) XOR operations are needed to conclude the match. In-

roducing this eyeball rotation correction was compulsory, and neglecting this compensation would lead to significant and unacceptable false rejections.

3. Iris Features Selection

Not all elements in \mathbb{B} are useful for iris recognition, and only a subset of the features in \mathbb{B} constitutes an optimal feature set \mathbb{B}^0 . However, simple selection of optimal features yields to a subset of coefficients indexed by selected scales and frequencies, but also by selected positions (angular and radial). There is however no rationale behind selecting only subsets of positions, as entire areas of both iris sectors are considered useful in the recognition.

Therefore, a two-stage procedure of Zak-Gabor-based iris features selection proposed in [2] is used in this work. In the first stage, the optimal parameter quadruples are selected that yield features maximizing the classification margin between the same and different irises. This is an exhaustive computation problem, yet many feature selection routines may be applied here (e.g., we may use Fisher's information related to each feature to sort them out and iteratively check the features' usefulness). In the second stage, it is checked how the scale-frequency pairs are populated by the optimal features (the more a scale-frequency pair is populated, the more it is significant in iris coding). The latter stage allows for selecting scales and frequencies optimal for a given database of iris images, being a good prediction of optimal scale-frequency pairs in iris recognition.

Peng *et al.* [7] proposed to use a *mutual information* (i.e., a Kullback-Leibler divergence of a product $P(X)P(Y)$ of two marginal probability distributions $P(X)$ and $P(Y)$ from the joint probability distribution $P(X, Y)$) to select best features employed in classification problems. Therefore, their selection criterion is based on the maximum statistical dependency between the variables X and Y . Due to difficulties in direct implementation of the maximum dependency condition, Peng *et al.* developed an equivalent form of this criterion, called the minimal-redundancy maximum-relevance (mRMR). In this paper we are applying the mRMR search methodology in the first stage to select the optimal feature set (instead of applying Fisher's information, as it was used in [2]). To make this process an automatic one, and to allow an easy adaptation of Zak-Gabor-based coding to various iris datasets, the methodology was integrated in the form of a convenient tool.

3.1. Estimation Database

Estimating optimal parameters for the Zak-Gabor-based coding requires suitable data. A database of 1000 iris images was collected by the station operated in similar environmental conditions, as the expected in final application, guarantying the appropriate quality of images. Twenty five volunteers, males and females, aged between 20 and

40 years, participated in the iris images acquisition process. The acquisition station was organized in a way that helped to take advantage of natural lighting to narrow the pupil. The quality of collected images was manually analyzed, and images of poor quality, or those generating segmentation failures were removed. Censoring, not carried out in system evaluation, is necessary when the optimal coding parameters have to be established. Any failures in delivering good quality data to the feature selection mechanism may have fatal consequences of selecting features not relevant to given iris tissue. Finally, in this work we use 946 samples representing 50 different eyes.

3.2. Stage I: Selection of Optimal Features \mathbb{B}^0

Zak-Gabor-based coding, being a member of wavelet packets family methods, analyses both the scale and frequency interdependently, so they should be considered simultaneously in feature selection. The optimal selection of features is complicated, since the most common frequencies that characterize all iris images cannot be guessed a priori due to significant and undetermined iris texture variability.

In general, when introducing new elements to the feature set, one expects the system to behave better in the sense of unambiguous biometric recognition. To assess the usefulness of a given feature (or feature set) we have to calculate, e.g., equal error rate (or a similar error measure, which is usually an increasing function of the feature set size), and compare the result with those obtained for alternative configuration of features. Single equal error rate may be obtained for a particular dataset of iris images, given the actual variant of the coding. This means that every selection of Zak-Gabor-based features requires recalculating all genuine and impostor scores. As the last step is extremely exhaustive, one may find alternative methods of feature usefulness assessment.

The mRMR method used in this paper, similarly to the routine employing Fisher's information, does not require calculation of the genuine and impostor scores each time we want to judge about the usefulness of a particular feature. A reference implementation of mRMR method has been made public [8], thus its incorporation into our feature selection tool was straightforward and it saved development time.

All features belonging to the set \mathbb{B} were sorted in descending order of their usefulness, expressed as their mutual information, ending up with a set $\mathbb{B}^{\text{sorted}}$. Then each first N' features constitute the intermediate iris binary template that is used in EER calculation. Note that during the search procedure required to sort elements of \mathbb{B} into $\mathbb{B}^{\text{sorted}}$ we need the genuine and impostor scores only when probing subsets of the sorted set of features, and not for all combinations of features.

The EER is one of many possible measures of a biometric system reliability. EER may be however useless when it falls to 0, thus we need other measure assessing the usefulness of a given set of features. For this purpose we

accumulate both sample mean and sample variances of comparison scores ξ in the form of the so-called *decidability factor* (*detectability* or *d-prime*), namely

$$d' = \frac{|\bar{\xi}_g - \bar{\xi}_i|}{\sqrt{\frac{1}{2}(\bar{\xi}_g + \bar{\xi}_i)}} \quad (8)$$

where $\bar{\xi}$ and $\bar{\xi}$ denote sample mean and sample variance of ξ , respectively. The further the mean values are located for same variances, the better is the separation of distributions. Similarly, keeping the same $\bar{\xi}_g$ and $\bar{\xi}_i$ and simultaneously narrowing $\bar{\xi}_g$ and $\bar{\xi}_i$ one may get higher level of distinction between genuine and impostor patterns. Consequently, the value of d' estimates the degree by which the distributions of ξ_g and ξ_i overlap (the higher d' is, the lower is the overlap).

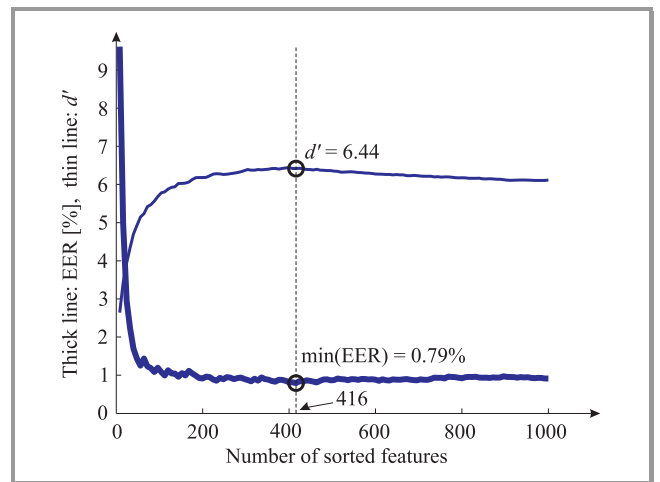


Fig. 2. EER (thick line) and decidability d' (thin line) vs. the number of sorted iris features. Best solution (minimizing the EER), achieved for first 416 features, and the corresponding d' are marked by circles.

Starting from a small number of best features from $\mathbb{B}^{\text{sorted}}$, we iteratively add new features (yet keeping the $\mathbb{B}^{\text{sorted}}$ order), each time building a new iris recognition system. According to observations (Fig. 2), the system reliability (in terms of the EER and d') first increases then deteriorates once the feature set enlarges, and the minimum EER = 0.79% for $N^0 = 416$ can be found. Figure 3 depicts the distribution of genuine and impostor scores achieved on the estimation database of iris images. The set \mathbb{B}^0 of optimal features is consequently used in the second stage, namely in the estimation of feature families (and the final iris coding configuration).

As each coefficient $a_{mk;sl}$ (and thus each feature in \mathbb{B}) is positioned within the iris sector, we may analyze a population of the iris sectors by selected features. Experiments show that the population of the iris sectors by their features is uneven, Fig. 4. Areas located in the middle of iris sectors are apparently more attractive, while the boundary parts are almost neglected by the feature selection methodology. This behavior related to the angular positions is easy

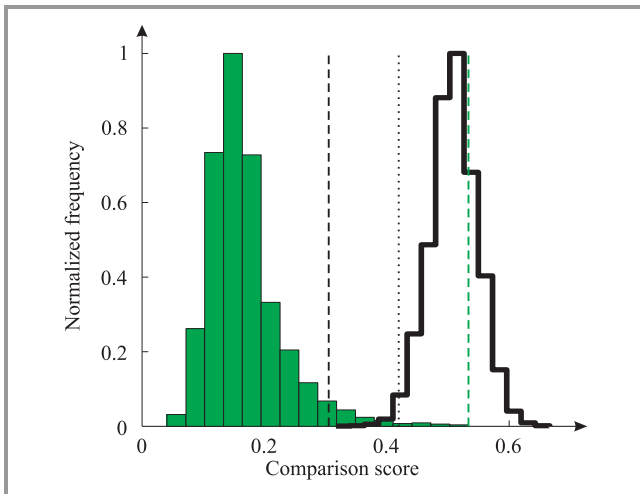


Fig. 3. Genuine (solid bars) and impostor (thick line) scores distribution achieved for a system variant employing 416 optimal features, i.e. the set \mathbb{B}^0 (cf. Fig 2). Dashed lines show the worst scores (minimum impostor and maximum genuine) and the dotted line points the acceptance threshold value set to calculate the EER.

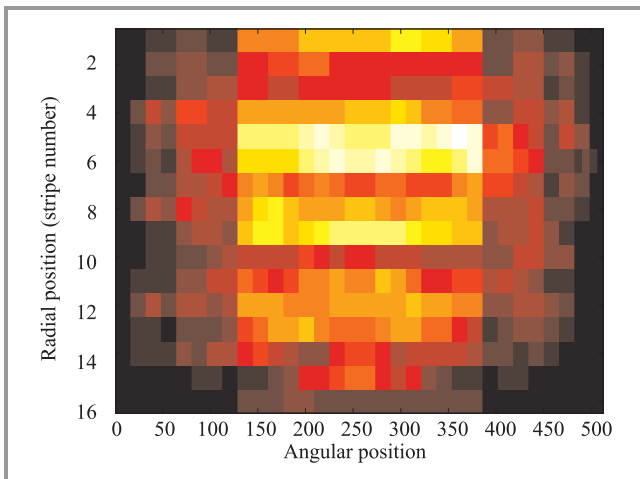


Fig. 4. The population of the iris sectors by their features. Values are averaged for two iris sectors, and lighter color denotes higher usage of the sector area in the optimal feature set \mathbb{B}^0 .

to be explained, as Zak-Gabor-based coding treats each iris stripe as a periodic function (this assumption comes from the principles of Zak's transform application). The same assumption, however, results in incorrect iris features calculated for non-continuity points at zero positions, i.e., features with weak abilities in distinguishing between same and different irises. Hence, the feature selection methodology correctly neglects those element of \mathbb{B} . However, the interpretation of the selection of middle elements in radial direction should refer to the anatomy of the iris, and the result may prove that the population of individual areas within the iris is uneven, with more discriminating parts located closer to the pupil than to the sclera. This interesting observation is worth of making further investigation, yet larger iris image datasets should be used.

3.3. Stage II: Selection of Optimal Feature Families \mathbb{B}^*

The second stage of feature selection, proposed for the Zak-Gabor-based coding, considers partitions of the set of all bits \mathbb{B} onto *feature families* $\mathbb{B}_{k,s}$, namely

$$\mathbb{B}_{k,s} = \{ \text{sgn}(\Re(a_{mk;s\ell})), \text{sgn}(\Im(a_{mk;s\ell})) : m = 0, \dots, M-1, \ell = 0, \dots, R-1 \}. \quad (9)$$

A single family collects all bits corresponding to the given frequency and scale indices, k and s , respectively. This second stage aims at searching the optimal frequencies and scales, and the previously determined set \mathbb{B}^0 is used to prioritize pairs (k,s) by their population of features from \mathbb{B}^0 .

Following [2], we plot the number of elements in the set $\mathbb{B}_{k,s} \cap \mathbb{B}^0$ separately for real and imaginary parts of the Zak-Gabor coefficients, Figs. 5 and 6.

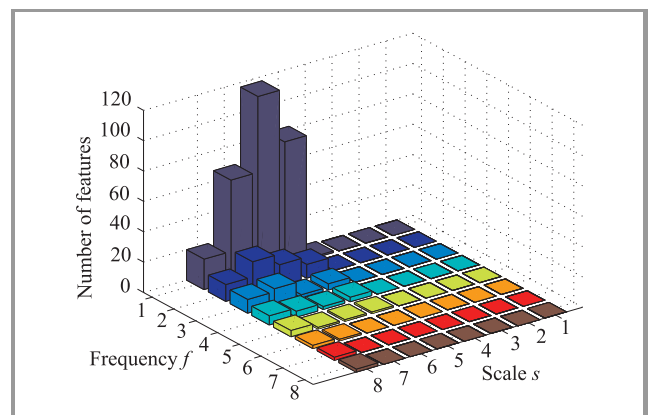


Fig. 5. A 2D histogram showing how families $\mathbb{B}_{k,s}$ are 'populated' by optimal features \mathbb{B}^0 determined for the imaginary part of Zak-Gabor coefficients.

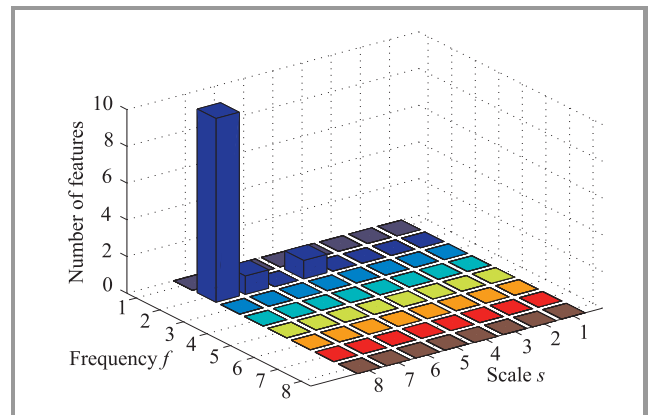


Fig. 6. Same as in Fig. 5 except that the real part of Zak-Gabor coefficients is used.

Note that the number of winning features is not identical for all families, which means that families differently contribute to the final discrimination capability of the resulting iris feature set. Thus the last step selecting the final set of families is required. Selecting the families of features may be done in various ways, and we use two variants of this selection. In the first variant we sort the families $\mathbb{B}_{k,s}$ by

the decreasing number of winning features \mathbb{B}^0 included in a given family, separately for real and imaginary parts of coefficients. This procedure prioritizes families that are most ‘populated’ by optimal features, and estimates each family’s usefulness. Including a new feature family into the final code results in a new iris recognition system that

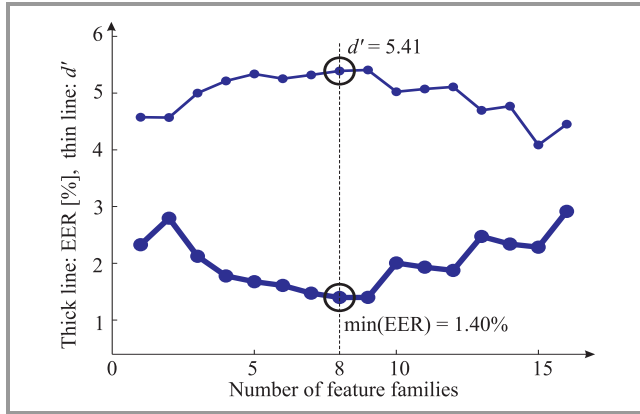


Fig. 7. EER (thick line) and decidability d' (thin line) versus the number of sorted iris feature families $\mathbb{B}_{k,s}$. Best solution minimizing the EER (achieved for the first 8 families) and the corresponding d' are marked by circles.

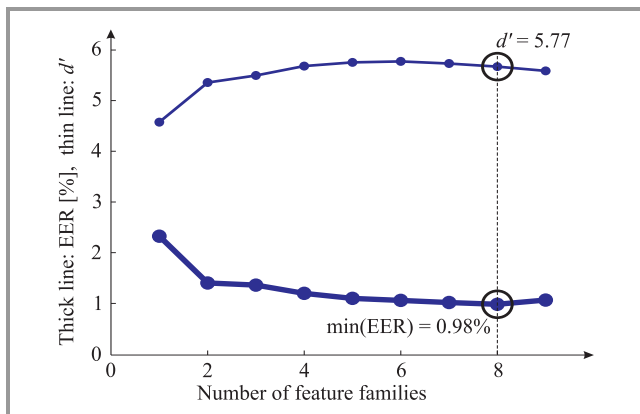


Fig. 8. Same as in Fig. 7 except that only families increasing the system’s accuracy are iteratively added to the final set.

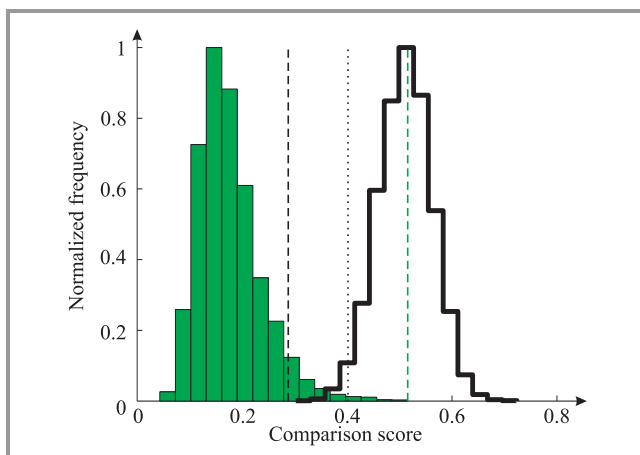


Fig. 9. Same as in Fig. 3, except that the optimal feature families \mathbb{B}^* are employed.

may be, as in the first stage, assessed by calculating EER (or additionally d'), Fig. 7. Families characterized by the minimum EER may be thus chosen and deliver the final configuration of the Zak-Gabor-based coding in this application.

However, one may observe that a few families increase the EER once they are added to the feature set. Thus the second variant of feature families selection adds only those $\mathbb{B}_{k,s}$ which increase system accuracy (i.e., decrease EER), Fig. 8. This variant results in best EER = 0.98% achieved for 8 families, constituting a set \mathbb{B}^* of 576 elements (i.e., bits of the code). Figure 9 presents the distribution of genuine and impostor scores obtained for the winning variant.

4. Implementation of the Automatic Iris Feature Selection Tool

For the convenience and repeatability of calculations in the first stage of the iris feature selection, an automatic iris feature selection tool is introduced. It is a hybrid environment where Matlab scripts manage executable programs written in C/C++. This conjunction gives flexibility of script implementation and easiness in replacing any element of the tool, if needed. All the calculations related to iris image processing (segmentation, Zak-Gabor-based feature extraction, iris template creation and matching) is realized by ACIrisSDK libraries [6], integrated into the tool.

The tool contains two main non-volatile file sets. The first one is the Iris Data Base (IDB) for which optimal encoding parameters are calculated. The second one is called Support Repository (SR) where processed intermediate objects are stored. IDB has a simple internal structure where images are located in folders named by user identifier and an indicator of the left/right iris. Because of the huge amount of data loaded to the tool, not all operations and its variables might be stored in the RAM simultaneously. Each phase of automatic feature selection collects needed data from the SR, processes it and puts back the results there.

In the first phase, the proposed tool performs iris segmentation of images stored in the IDB. For each representation, the implementation of methods described in Subsection 2.1 provides the set of segmentation coordinates: centers of circles approximating inner and outer boundaries of the iris, detected occlusions and sectors chosen for features calculation. The results in a serialized form are placed as files in the SR.

Images stored within the IDB includes samples that contain distortions typical for iris image acquisition (e.g., blurred images, half-closed eye or incorrect cropping). To ensure the highest quality of the used data, a simple and heuristic algorithm of best samples selection is also build-in in the proposed tool. Namely, for each iris image two kinds of biometric templates are calculated: the enrollment template and the verification template. These templates are matched within the iris class. The results are collected

and these irises which are not matched to some (experimentally determined) number of other are rejected from further processing. This simple mechanism automatically finds outliers within a class, i.e., images of significantly worse quality than the remaining in the class. If necessary, other poor quality images, not rejected automatically, may be removed manually.

Third phase concerns calculation of a full Zak-Gabor-based feature set for each iris that was not rejected during previous stage. Before that, a very last distortion must be compensated. When the image of the eye is taken, there is a possibility of unintentional tilt of the camera or the object's head. The best way of fixing this problem is to shift the polar iris images in angular direction with a simultaneous checking of their correlation. The highest obtained correlation determines the angle for tilt correction of one iris in relation to the others. Then the configuration that minimizes the average tilt correction angle is selected, and all polar images are modified this way. During the next step, based on shifted polar images, the full Zak-Gabor-based feature set \mathbb{B} is calculated for each iris and stored in the SR separately.

The final phase begins with aggregation of calculated feature sets into one matrix. First row of this matrix contains feature indices, and the remaining rows are composed with the iris class index, and values of its Zak-Gabor-based features. This matrix is an input for chosen mRMR method used for feature selection. The output is a set $\mathbb{B}^{\text{sorted}}$ of feature indices sorted by decreasing usefulness.

The proposed feature selection tool was previously used to estimate Zak-Gabor-based features (and coding parameters) for a few databases, e.g., publicly available Bath Iris Image Database, and our proprietary databases: BioBase collected by an IrisCUBE camera [2], and DatastripBase collected by a Datastrip DSV2+TURBO-SC mobile camera. The estimated time needed for feature selection for 1000 images is approximately 8 hours (assessed when running on the machine with Intel®Core i5 processor, equipped with 4 GB of RAM).

5. Implementation of the Secure Biometric Verification Station

Secure biometric verification station (SBS) is designed to be a part of a larger system [9], consisting of one or more external PC units, which send requests of user's identity biometric verification. In the following subsections, we present the hardware and software components, respectively.

5.1. Hardware Specification

For the purpose of the station development we used a conjunction of two ready-to-use devices. The first one, *Kontron Micro Client IIA 70* is a fanless microcomputer equipped with the Intel®Atom™N270 1.6 GHz CPU, 2 GB of RAM

and 8 GB of a Compact Flash memory, a 7.0" TFT LCD touch screen, USB and LAN 10/100/1000 interfaces and Kontron customized Windows XP Embedded. This configuration provides a compact and fully functional environment for Windows based x86 applications.



Fig. 10. Components of the developed station: a processing unit with a display for communication with a subject and an iris capture camera.

Second device, *Corvus Vista FA2*, is a face and iris capture camera. Connected to the Kontron microcomputer with USB 2.0 interface guarantees fully automated capturing of iris images compliant with ISO/IEC requirements [4] at the resolution of 640×480 pixels. The iris camera is equipped with multi-wavelength IR illuminants, a distance-sensed auto focusing system and the LED-based feedback for captured subjects convenience. Provided SDK for C/C++ enables also gaining RGB face images (up to 2048×1536 pixels) and setting basic illumination adjustments for both images acquisition modes. Figure 10 shows hardware components of the station (intentionally presented without casing).

5.2. Software Functional Requirements and Implementation

Designing the secure biometric verification station induces a few security, comfort and simplification aspects to be considered. In particular they concern:

- secure protocol of communication with an external unit,
- clear and understandable Graphical User Interface,
- proper iris image acquisition,
- internal data organization system,
- handling of biometric processes.

The implementation of the proposed station functionality is divided into individual components, Fig. 11. They are designed as follows:

- **SBS** – exports three main biometric functions (SBS_Enroll, SBS_Verify, SBS_Delete) in a form of Dynamic-Link Library (DLL); SBS integrates also the remaining components;

- **GUI** – handles the Graphical User Interface;
- **FILE SYSTEM** – contains necessary files (GUI items, users biometric templates and log files) in a specially designed folder structure;
- **BIOMETRICS** – provides biometric operations with the use of ACIrisSDK libraries, including creating and matching of user templates stored in the OS file system;
- **CORVUS VISTA FA2** – provides communication and control over the iris camera used.

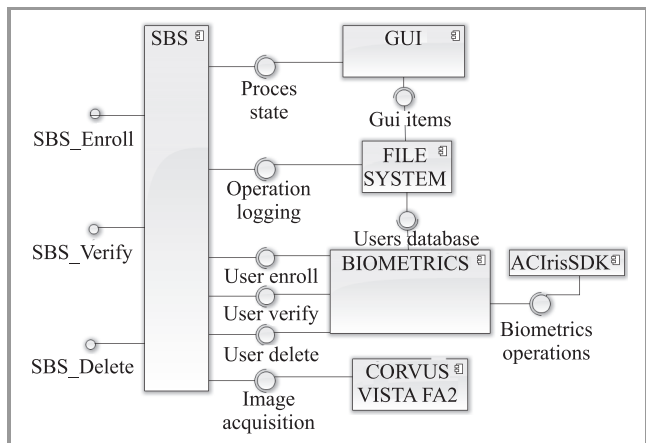


Fig. 11. Component diagram of the SBS software modules.

Communication protocol. Cooperation with any other PC unit (even in the immediate vicinity) requires establishing a secure communication between these two machines. If a communication channel is not appropriately protected, any biometric data transmitted may be stolen or modified. To prevent the system from abuses, special communication protocol is developed.

For flexibility in developing of the proposed solution, a communication layer is separated from the verification procedure, in particular from handling biometric devices, controlling acquisition processes and data processing (templates creation and matching), as well as database and errors logging. To achieve this goal, all non-communication functionality is supplied in C/C++ Dynamic-Link Library (DLL) which provides three general functionalities: new user enrollment, user verification, and deleting users data from the system.

Graphical User Interface with Qt. Neither enrolling to the system nor verifying the user is an atomic process. Both processes consist of several stages where each of them may take some time and result in an error or warning. Therefore, for making a proposed solution more user friendly, we also introduce Graphical User Interface (GUI) implemented in Qt 4.7 technology, and fully compatible with the provided 7" LCD touch screen of the microcomputer. The Information about the type of current process, its result and commands may be displayed in a clear form to the user. In

the presented solution, there is no need for a user to input any information using the screen, mouse or keyboard, besides presenting the iris after the message. This is due to controlling current biometric processes by the external unit.

Iris image acquisition. Prepared solution contains necessary functionality (based on the Corvus Vista FA2 vendor’s SDK) for ensuring proper device initialization, handling of image capture timeouts, illumination adjustments and terminating of the connection with the camera, after receiving captured iris images. The procedure of iris capture is fully automatic. Provided SDK uses build-in distance sensor for estimating face position in front of the lens, it controls the NIR illuminants for appropriate scene illumination and corrects sharpness of the image. The quality of the iris image is assessed on-line, and when it is acceptable the capture process terminates, sensor and illuminants are set off, and the image is available in the indicated memory buffer.

Users database and log files. In order to be simple, biometric templates, logging results and selected GUI elements are stored in a local nonvolatile memory. There is no need for installing detached Database Management System (DBMS) (like *mysql* or *Microsoft SQL Server*) as the user database structure is defined by biometric templates, serialized to binary files placed in the USERS local folder, and the configuration data is kept within the CONF local folder. Users can be added and removed only upon the external unit secured request. The station implements a simple logging mechanism. The results of component functions along with threat level (one of six possible), time stamp (set with thousandth of a second precision), associated user ID information and a message with a description are appended to a text file (named by daily date) in the LOG folder.

Biometric operations. The main software component of the station is responsible for biometric operations, i.e., enrolling new users and verifying them upon the request of the external unit. The enrollment process starts with checking of the possibility of adding a new user (specified by UID). It may not be possible when the maximum number of registered users has been reached or indicated that the UID already exists. In the latter case, the request is revoked and no further action is taken. Otherwise, three enrollment iris images are captured (each after a specified time interval), the biometric template is created, and it is placed under provided UID in the user database. If timeout occurs during the acquisition of images, but at least one image was captured, template can still be created with the obtained samples. The enrollment process is also revoked when no image is captured.

At the verification stage, only one image on the eye is captured, and temporarily created verification template is matched with the enrollment template stored in the user database (if UID provided is registered within the database).

Verification result is displayed on the LCD ('MATCH/NO MATCH') and it is sent to the external unit requesting the verification.

The enrollment process takes typically one minute (including capturing of three iris images, template creation and its storage) and the verification process does not exceed a second, which very favorably compares to the most of commercial iris recognition systems.

6. Summary

This paper describes an application of the well-established Zak-Gabor-based iris coding to build a secure verification station. To adapt the coding parameters (i.e., iris feature families, corresponding to frequencies and scales of wavelets emphasizing individual iris features) we used the mRMR method using the mutual information as an indicator of the iris feature usefulness. To make the selection process an automatic one, the iris feature selection tool was designed and built. A database of iris images collected by the developed station was used to automatically adapt the iris coding to the quality of iris images employed. The feature selection tool allowed for convenient adaptation of the Zak-Gabor-based method parameters (in a reasonable time of several hours) and a promising EER = 0.98% was achieved for iris images collected by the designed verification station.

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