Two different approaches for iris recognition using Gabor filters and multiscale zero-crossing representation

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Abstract

Importance of biometric user identification is increasing everyday. One of the most promising techniques is the one based on the human iris. The authors, in this work, describe different approaches to develop this biometric technique. Based on the works carried out by Daugman, the authors have worked using Gabor filters and Hamming distance. But in addition, they have also worked in zero-crossing representation of the dyadic wavelet transform applied to two different iris signatures: one based on a single virtual circle of the iris; the other one based on an annular region. Also other metrics have been applied to be compared with the results obtained with the Hamming distance. In this work Euclidean distance and $d_z$ will be shown. The last proposed approach is translation, rotation and scale invariant. Results will show a classification success up to 99.6\% achieving an equal error rate down to 0.12\% and the possibility of having null false acceptance rates with very low false rejection rates.

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1. Introduction

As it is well-known, biometrics deals with identification of individuals based on their biological and/or behavioral features. Technologies that exploit biometrics have the potential application of identifying individuals in order to control access to secured areas or services. Nowadays a lot of biometric techniques are being developed based on different features and algorithms [1]. Each technique has its strengths and limitations, not being possible to determine which is the best without considering the application environment. Nevertheless, it is known that, from all of these techniques, iris recognition is one of the most promising for high security applications [2]. Human iris is an overt body, protected by the cornea and highly distinctive to an individual. The possibility that the human iris might be used as a kind of optical fingerprint for personal identification was suggested originally by ophthalmologists. Some time ago, only two prototype iris-recognition systems had been developed: one by Daugman [2], whose algorithms for iris recognition are more detailed in [3], and the other one by Wildes et al. [4]. More recently we can find some works in this issue such as [5–7] based on texture analysis, [8] using 2D Hilbert transform, [9] using wavelet transform, and [10,11] where Gabor filters are used.

In this paper the authors describe two different approaches of our iris recognition system, the first one based on Gabor
filters and Hamming distance, the second one using discrete wavelet transform zero-crossing representation of two different kind of iris signatures, previously defined. We also have carried out a quantitative comparison using different metrics in order to check the performance of two approaches. An explanation of all the different blocks of each iris biometric approach designed will be given. Thus, the paper is organized as follows. Section 2 presents the image capture block, including pre-processing. Section 3 covers the feature extraction block, detailing each of the three methods used. Next, in Section 4, the classification and verification problem will be studied, including the similarity distances adopted. Experimental results, detailing the database and final results, are shown in Section 5, including a comparison of the results provided with different approaches. Conclusions, according to the results obtained, will close the paper.

2. Image acquisition and pre-processing

Due to the transparency of the cornea, any video or photographic device could be used to obtain an image of the iris. In our system, a high resolution digital photo camera has been used, obtaining a high quality image with the minimum loss of information. Future work will use capture devices such as video cameras and infrared light. Special optics are applied to have a zoom that enables the capture of the image of the iris from a distance large enough to avoid any user rejection. Thus, a photograph is taken, covering the whole eye of the user (Fig. 1(a)).

After the capture, the localization of the iris inside the image is performed. First, the image of the eye is converted to gray scale and its histogram is linearly stretched, as to be able to take profit of all range given by the 256 levels of the gray scale. Then, following the ideas proposed by Daugman in [2], a grid is placed over the image and testing each of the points in the grid, the center of the iris, as well as the outer boundary; i.e., the border between the iris and the sclera, is detected making use of the circular structure of the latter. The detection is performed maximizing $D$, where

$$ D = \sum_{m} \sum_{k=1}^{5} (I_{n,m} - I_{n-k,m}), $$

being

$$ I_{i,j} = I(x_0 + i \Delta_r \cos(j \Delta_\theta), y_0 + i \Delta_r \sin(j \Delta_\theta)), $$

where $(x_0, y_0)$ is a point in the grid taken as center, $\Delta_r$ and $\Delta_\theta$ are the increments of radio and angle, and $I(x, y)$ is the gray level of the image at pixel $(x, y)$.

Once the outer bounds of the iris are detected (Fig. 1(b)), the biggest square inside the circle of the iris is taken, and

![Fig. 1. (a) Photograph taken; (b) Outer boundary detection; (c) Inner boundary detection; (d) Isolated iris image.](image-url)
the same process is performed in order to find the inner boundary; i.e., the frontier between the iris and the pupil (Fig. 1(c)). The points inside this last border are also suppressed, obtaining the image shown in Fig. 1(d). In the last step of the pre-processing block, the image of the isolated iris are scaled to achieve a constant diameter regardless of the size in the original image.

3. Feature extraction

Throughout this section, the different feature extraction algorithms used will be described. First, the scheme based on Gabor filters will be shown, followed by a subsection explaining the multiscale zero-crossing representation version. The latter subsection will describe the iris signature taken from a virtual circle followed by the iris signature obtained from an annular region, and finally the multiscale zero-crossing representation.

3.1. Gabor filters

The first step in the feature extraction block of the system based on the Gabor filters [12,13] is a transformation of the image. In this transformation the superior and inferior cones of the iris are eliminated, and the differences in the size of the iris are compensated through a polar sampling of the image, obtaining \( J \) as a result. The equation system used for this transformation is the following:

\[
J(\rho, \phi) = I_E(x_0 + r \cos \theta, y_0 + r \sin \theta),
\]

being

\[
r = r_i + (\rho - 1)A_r, \quad \forall \rho \in \mathbb{N} : \rho \leq \frac{r_e - r_i}{A_r},
\]

\[
\theta = \begin{cases} 
-\frac{\pi}{\Delta \theta}, & \text{if } \phi \leq \frac{\pi}{2\Delta \theta}, \\
\frac{\pi}{\Delta \theta}, & \text{if } \phi \leq \frac{\pi}{2\Delta \theta}, \\
\frac{\pi}{\Delta \theta} + (\phi - 1), & \text{if } \phi > \frac{\pi}{2\Delta \theta}, \\
\frac{\pi}{\Delta \theta}, & \text{if } \phi > \frac{\pi}{2\Delta \theta},
\end{cases}
\]

where \( I_E \) represents the gray levels of the iris image with the sclera and pupil extracted, \( r_i \) and \( r_e \) are the inner and outer radius, \((x_0, y_0)\) is the center of the pupil, and \( A_r \) and \( A_\theta \) are the sample intervals in magnitude and angle.

Following [2], the image of the iris pre-processed, \( J \), is weighted with the imaginary part of a Gabor filter [12,14], used in four orientations (0, \( \pi/4 \), \( \pi/2 \) and \( 3\pi/4 \)). In order to perform this operation, the image is divided in squared sections and the following equation is applied:

\[
c(i,j) = \sum_{x=1}^{N} \sum_{y=1}^{M} J(i+x-N/2, j+y-M/2) \times g(x, y, \phi_k, \lambda),
\]

being

\[
g(x, y, \phi_k, \lambda) = \exp \left\{ -\frac{1}{2} \left[ \frac{(x \cos \phi_k + y \sin \phi_k)^2}{\sigma^2_x} + \frac{(-x \sin \phi_k + y \cos \phi_k)^2}{\sigma^2_y} \right] \right\} \times \frac{1}{\lambda} \sin \left\{ \frac{2\pi(x \cos \phi_k + y \sin \phi_k)}{\lambda} \right\}. \quad (6)
\]

In these equations, the dimension of the filter is \( N \times M \), \((i, j)\) is the center of each section and \( \phi_k, \lambda, \sigma_x \) and \( \sigma_y \) are the parameters of the filter, meaning orientation, scale and deviations in \( x \) and \( y \), respectively. The number of sections chosen, will determine the size of the feature vector [1]. More details are given in Section 5.

3.2. Multiscale zero-crossing representation of iris signature

3.2.1. Iris signature from an iris virtual circle

In our biometric system based on the discrete wavelet transform zero-crossing representation, the first step of the feature extraction block is to obtain a set of data (which will be referred as iris signature \( IS \)) from each isolated iris sample which allows a suitable extraction of its features. In this way, following [9], we consider the first definition of iris signature. The centroid of the detected pupil is chosen as the reference point for obtaining this data set. Thus, the iris signature will be the gray level values on the contour of a virtual circle, which is centered at the centroid of the pupil, with fixed radius \( r \) and considering angular increments of \( 2\pi/L_s \), being \( L_s = 256 \), the length of iris signature (previously fixed); i.e.,

\[
IS = I_E(x_c + r \cos \theta, y_c + r \sin \theta),
\]

being

\[
2\pi/L_s \leq \theta \leq 2(n + 1)\pi/L_s, \quad n \in \mathbb{N} \cup \{0\},
\]

\( r \) a fixed radius and \((x_c, y_c)\) the centroid of the pupil. Fig. 2 shows a sample iris signature.

3.2.2. Iris signature from an iris annular region

In the second version of our biometric system based on multiscale zero-crossing representation, we also consider the centroid of the detected pupil as the reference point for obtaining this data set, and we propose a new definition of iris signature as follows: record the gray level values on each contour of a virtual circle, centered at the centroid of the pupil with radius \( r \), such that \( r_1 \leq r \leq r_e \), being \( r_1 \) and \( r_e \) two radius given (Fig. 3(a)), and considering angular increments of \( 2\pi/L_s \), being \( L_s = 256 \) the length of sequence (previously fixed), for sampling the data points. Finally, the data set
which we will denote as *iris signature* ($I_S$) is calculated as

$$I_S = \frac{1}{r_e - r_i + 1} \sum_{r=r_i}^{r_e} I_E(x_c + r \cos \theta, y_c + r \sin \theta), \quad (8)$$

being

$$2n\pi/L_s \leq \theta \leq 2(n + 1)\pi/L_s, \quad n \in \mathbb{N} \cup \{0\}.$$  

In Fig. 3(b), we can see a sample *iris signature* corresponding to isolated iris sample shown in Fig. 1(d), considering this new definition.

### 3.2.3. Multiscale zero-crossing representation

In order to use the iris pattern for identification, it is important to define a representation that is well adapted for extracting the iris information content from iris signatures. In this way, we introduce an algorithm for extracting unique features from iris signatures and representing these features using discrete dyadic wavelet transform given in [15].

When a signal includes important structures that belong to different scales, it is often helpful to reorganize the signal information into a set of “detail components” of varying size. It is known that one can obtain the position of multi-scale sharp variations points from the zero-crossing of the signal convolved with the laplacian of a Gaussian [16]. This procedure has been used in many pattern recognition applications, such as, in character recognition [17], in iris texture feature representation [18], in pattern recognition of EGG signals [19], in recognition of 2-D object contours [20], in edge detection schemes [21–24] and its applications to detection of anomalies in medical images [25,26], etc. More general applications of wavelet transform to pattern recognition can be found in [27–29].

Let $f(x) \in L^2(\mathbb{R})$ and $\{W_{2^j} f(x)\}_{j \in \mathbb{Z}}$ be its dyadic wavelet transform [30]. For any pair of consecutive zero-crossings of $W_{2^j}$ whose abscissae are respectively $(z_n - 1, z_n)$, we record the value of the integral

$$e_n = \int_{z_n}^{z_n - 1} W_{2^j} f(x) \, dx. \quad (9)$$

For any function $W_{2^j} f(x)$, the position of the zero-crossings $(z_n)_{n \in \mathbb{Z}}$ can be represented by a piece-wise constant function

$$Z_{2^j} f(x) = \frac{e_n}{z_n - z_n - 1}, \quad x \in [z_n - 1, z_n]. \quad (10)$$

Therefore, in order to obtain a complete and stable representation, we consider the zero-crossing of the dyadic wavelet transform of the *iris signature* ($I_S$); i.e., instead of considering the zero-crossing of a wavelet transform on a continuum of scales, we restrict ourselves to dyadic scales $2^j, j \in \mathbb{Z}$, and we also record the value of the wavelet transform between two consecutive zero-crossings.

In practical implementations, the input signal, in our case the iris signature, is measured with a finite resolution that imposes a finer scale when computing the dyadic wavelet transform, and we cannot compute the wavelet transform at

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**Fig. 2.** Sample iris signature corresponding to isolated iris sample shown in Fig. 1(d).

**Fig. 3.** (a) Annular region (from Fig. 1(d)) considered for finding the iris signature shown in (b).
all scales $2^j$ for $j$ varying from $-\infty$ to $+\infty$. We are limited by a finite larger scale and a nonzero finer scale. Let us suppose for normalization purposes that the finer scale is equal to 1 and that $2^J$ is the largest scale. Therefore, we can obtain the discrete dyadic wavelet transform of $I_S$

$$\{S_{2^j}(I_S), (W_{2^j}(I_S))_{1 \leq j \leq J}\},$$

where $S_{2^j}(I_S)$ is the coarse signal and $(W_{2^j}(I_S))_{1 \leq j \leq J}$ can be interpreted as the discrete details available when smoothing $I_S$ at the scale 1 but which have disappeared when smoothing $I_S$ at the larger scale $2^J$. Zero-crossing of $(W_{2^j}(I_S))_{1 \leq j \leq J}$ are estimated from sign changes of its samples. The position of each zero-crossing is estimated with a linear interpolation between two samples of different sign. Therefore, if $I_S$ has $N$ nonzero samples, since there are at most $N \log(N)$ samples in its discrete wavelet representation, the number of operations to obtain the position of the zero-crossing is $O(N \log(N))$. Therefore, we consider as the discrete zero-crossing representation of $I_S$ the set of signals

$$\{(Z_{2^j}(I_S))_{1 \leq j \leq J}\}. \tag{12}$$

We have excluded the coarsest level in order to obtain a robust representation in a noisy environment and reduce the number of computations required, since information at fine resolution levels is strongly affected by noise and quantization errors which are due to the use of a rectangular grid in digital images [20]. Thus, to reduce such effects on the zero-crossing representation a few low resolution levels, excluding the coarsest one, will be used. In this work, the four lowest resolution levels, excluding the coarsest, have been used; i.e., $3 \leq j \leq 6$.

As an example, we show in Fig. 4(a) the four lowest resolution levels of the discrete dyadic wavelet transform of the iris signature considering the second version; i.e., using an annular region of the sample iris. Fig. 4(b) shows the zero-crossing representation corresponding to the lowest four resolution levels of the wavelet transform previously calculated.

The dyadic wavelet used in this work is the quadratic spline of compact support defined in [30]. The advantage of using this function is that it has a finite support and it also has a smaller number of coefficients than those of the second derivative of a smoothing function [16].

4. Classification and verification

All the features obtained should enter a comparison process to determine the user whose iris photograph was taken. This comparison is to be made with the user’s template, which will be calculated depending on the comparison algorithm used. The experiments are completed in two modes: classification (one-to-many matching) and verification (one-to-one matching), and the following different metrics have been used:

- The Euclidean distance, considered as the most common technique of all, performs its measurements with the following equation:

$$d_E(y, p) = \sqrt{\sum_{i=1}^{L} (y_i - p_i)^2}, \tag{13}$$

being $L$ the dimension of the feature vector, $y_i$ the $i$th component of the sample feature vector, and $p_i$ the $i$th component of the template feature vector.

- The binary Hamming distance

$$d_H^n(y, p) = \frac{1}{L} \sum_{i=1}^{L} y_i \oplus p_i, \tag{14}$$

where $\oplus$ denotes Exclusive-OR, does not measure the difference between the components of the feature vectors, but measures the number of components that differ in value. Based on the assumption that the feature components follow a Gaussian distribution, not only the mean of the set of initial samples is obtained, but also a factor
of standard deviation of the samples. In the comparison process, the number of components of the feature vector falling outside the area defined by the template parameters is counted, obtaining the Hamming distance
\[ d_H(y, p) = \# \{ i \in \{1, \ldots, L\} : |y_i - p_i^m| > p_i^R \}, \]
where \( y_i \) is the \( i \)th component of the sample vector, \( p_i^m \) is the mean for the \( i \)th component, and \( p_i^R \) the factor of the standard deviation for the \( i \)th component.

- Finally, we describe a distance directly related with the zero-crossing representation of a 1-D signal [20]. Let us denote the zero-crossing representation of an object \( y \) at a particular resolution level \( j \) by \( Z_j y \). Also, let \( X_j = \{ x_j r; r = 1, \ldots, R_j \} \) be a set containing the locations of zero-crossing points at level \( j \), where \( R_j \) is the number of zero-crossings of representation at this level. Then, the representation \( Z_j y \) can be uniquely expressed in the form of a set of complex numbers, which can be written as a set of ordered pairs \( (\mu_j y, \rho_j y) \), whose imaginary, \( \rho_j y \), and real, \( \mu_j y \), parts indicate the zero-crossing position and magnitude of \( Z_j y \) between two adjacent zero-crossing points, respectively. Thus, we consider the following dissimilarity function which compares the unknown object \( y \) and candidate model \( p \) at a particular resolution level \( j \)
\[ d_j(y, p) = \sum_{i=1}^{R_j} \left| (\mu_j y)_i (\rho_j y)_i - \Gamma (\mu_j p)_i (\rho_j p)_i \right|^2, \]
where \( \Gamma \) is the scale factor and equals the ratio between the average radius of the candidate model and that of the unknown object. Note that this function is computed using only the zero-crossing points. The overall dissimilarity value of the unknown object and the candidate model over the resolution interval \([K, M]\) will be the average of the dissimilarity functions calculated at each resolution level in this interval; i.e.,
\[ d_Z(y, p) = \sum_{j=k}^{M} \frac{d_j(y, p)}{K - M - 1}. \]

5. Experimental results

This section reports some experimental results obtained with each one of different approaches developed here, detailing the database used, the enrollment process, and final results in classification; i.e., in a biometric recognition scheme, and in verification; i.e., in a biometric verification scheme. Finally, a comparison between the results obtained is given.

Results have been obtained using a database of both eyes of 50 people and, at least, 30 photos of each eye. The photographs were taken in different hours and days, during 11 months. Each eye was considered as “of a different person”; i.e., each person has two identities, the one of the left eye and the one of the right one. That makes 100 “virtual” different users.

5.1. Results in classification

As stated above, the authors have studied the different methods developed, not only in verification, but also in classification. Results obtained in classification are presented in the following subsections.

Experiments in classification have not consider any kind of full rejection threshold, so although an image could have a matching rate really low, if it is the highest over all users, it is not rejected but considered as a misclassification.

5.1.1. Results using Gabor filters

Considering the approach based on Gabor filters, the performance of the system has been made considering four sizes of the feature vector (from 256 to 1860 bits), obtained as it is shown in Table 1.

<table>
<thead>
<tr>
<th>Dimension</th>
<th>( \Delta t )</th>
<th>Overlap in ( J_x )</th>
<th>Overlap in ( J_y )</th>
</tr>
</thead>
<tbody>
<tr>
<td>256</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>512</td>
<td>0.5</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>992</td>
<td>1</td>
<td>0</td>
<td>50%</td>
</tr>
<tr>
<td>1860</td>
<td>1</td>
<td>50%</td>
<td>50%</td>
</tr>
</tbody>
</table>

5.1.2. Results using zero-crossing representation

In order to apply the binary Hamming distance to feature vector provided by the two versions of the second approach, we define the expanded feature vector as a binary sequence obtained as follows: for each scale, we define that the values of this binary sequence are set to 1 if the value of

<table>
<thead>
<tr>
<th>Template size (bits)</th>
<th>Classification success (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>256</td>
<td>95.3%</td>
</tr>
<tr>
<td>992</td>
<td>98.3%</td>
</tr>
<tr>
<td>1860</td>
<td>98.3%</td>
</tr>
</tbody>
</table>
zero-crossing representation of the iris signature is positive or null, otherwise 0. Thus, considering four scales, and 256 bits per scale, the feature vector is a binary sequence of 1024 bits.

For this approach, an analysis has been made for the different distances previously presented and considering the iris signature obtained from a virtual circle or from an annular region, obtaining the results shown in Table 3. It can be seen that binary Hamming distance, applied to expanded feature vector corresponding to an iris signature obtained from an annular region, and considering \( r_i = 5 \) and \( r_e = 45 \), provides optimal results, achieving a 99.6% of classification success, while the \( d_Z \) and Euclidean distances achieve a 95.6% and 95.0% of success, respectively. On the other hand, we can also see that binary Hamming distance applied to expanded feature vector corresponding to the iris signature from a virtual circle provides a good result, even though worse than previous one, achieving a 97.6% of classification success, while the \( d_Z \) and Euclidean distances achieve a 95.3% and 94.3% of success, respectively. These results demonstrate the uniqueness of the iris features extracted. Also these prove that each iris of a single person have different characteristics, which leads to different features extracted.

<table>
<thead>
<tr>
<th>Distance</th>
<th>Using an iris virtual circle (%)</th>
<th>Using an iris annular region (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Euclidean</td>
<td>94.3%</td>
<td>95.0%</td>
</tr>
<tr>
<td>Hamming</td>
<td>97.6%</td>
<td>99.6%</td>
</tr>
<tr>
<td>( d_Z )</td>
<td>95.3%</td>
<td>95.6%</td>
</tr>
</tbody>
</table>

Table 3: Results in classification using an iris virtual circle or an iris annular region

5.2. Results in verification

As it is well known, in a verification architecture, the performance can be measured in terms of three different rates: false acceptance rate (FAR), false rejection rate (FRR) and equal error rate (EER) (i.e., the value where the FAR and FRR rates are made equal by adjusting the decision threshold). For each of the metrics used, a threshold is defined to decide whether the user is accepted or rejected. Varying this threshold different values of FRR and FAR are obtained.

5.2.1. Results using Gabor filters

Using the approach based on the Gabor filters, and considering the four sizes of the feature vector and the binary Hamming distances, the results obtained in biometric verification are shown in Fig. 5. They show that, in all cases, the EER; i.e., the cross point between the FAR and the FRR curves, is always below 10%, achieving a 3.3% for 1860 bits. We can also see that a null FAR has been obtained for very low rates of false rejection, which means that this system is optimal for very high security environments.

Furthermore, the FRR can be lowered, using the system as a 3-try-rejection system; i.e., rejecting an user after 3 consecutives errors (as it happens with a credit card in an automatic teller machine).

5.2.2. Results using zero-crossing representation

In this case, binary Hamming distance still provides the best results. Thus, considering this approach based on the iris signature from an annular region (with \( r_i = 5 \) and \( r_e = 45 \)) as a verification system, we obtain the results shown in Fig. 6. In Fig. 6(a), we can see that binary Hamming distance, applied to the corresponding expanded feature vector, shows better results, achieving an EER of 0.12%. But what is
more important, is that once more, a null FAR has been obtained for very low rates of false rejection. Results obtained using Euclidean and $d_Z$ distances are shown in Fig. 6(b), where it can be seen that EER achieves a 2.44% using Euclidean distance and a 2.12% using $d_Z$ distance. This means a great improvement of the best results obtained with Gabor filters.

Finally, considering the iris signature from a virtual circle, the binary Hamming distance provides good results, but also worse than previous version. It can be seen in Fig. 7(a) that EER achieves a 0.22%, and a null FAR has been obtained for very low rates of false rejection. Results obtained using Euclidean and $d_Z$ distances are shown in Fig. 7(b), where it can be seen that EER achieves a 1.53% using Euclidean distance and a 2.35% using $d_Z$ distance.

The above experiments are performed in Matlab 5.3 on a 500 Mhz PC. Table 4 illustrates the computational cost of three methods, including the CPU time for feature extraction and matching. As we can see the system based on zero-crossing representation using an iris annular region consumes: (1) less time than the method based on Gabor filters (for 1860 bits) and (2) similar time than the same method using an iris virtual circle, with the advantage that proposed system provides optimal results.
6. Conclusions

In this paper, the authors have developed several iris recognition approaches and have obtained a series of results to show the performance of each approach. Three different feature extraction algorithms have been used; one of them based on Gabor filters, while the other two based on zero-crossing representation of a discrete dyadic wavelet transform. Also, each of those algorithms have been tested with three different pattern recognition methods, based on three distances: Euclidean, Hamming and $dZ$. Experimental results have shown that the best metric in all cases is the Hamming distance, obtaining really good results for each of the three feature extraction algorithms. Nevertheless, it is important to emphasize that in both schemes, classification and verification, better results have been obtained with iris recognition system based on multiscale zero-crossing representation using proposed iris signature (calculated from an annular iris region) and binary Hamming distance, with a 99.6% of classification success and an EER down to 0.12%, which means that this system is optimal for very high security environments. Actually, we are working in increasing database in order to carry out a performance comparison more extensive of three approaches, since the results until now obtained are highly encouraging.

References


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