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Continuous versus exclusive classification for fingerprint retrieval

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Abstract

This work addresses the problem of fingerprint retrieval in a large database. Traditional approaches adopt exclusive classification of fingerprints; the paper shows that a continuous classification can improve the performance of fingerprint retrieval tasks significantly. The proposed approach is based on the extraction of numerical vectors from the directional images of the fingerprints; the retrieval is thus performed in a multidimensional space by using similarity criteria. © 1997 Elsevier Science B.V.

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1. Introduction

Fingerprint recognition is the basic task of the Integrated Automated Fingerprint Identification Service (IAFIS) of the most famous police agencies (Lee and Gaensslen, 1991). *Ten-print based identification* and *latent fingerprint recognition* are the two in concerns of an IAFIS. In the former, the system should identify a person by the whole sequence of his/her ten fingerprints, in the latter it has to identify a person through a latent fingerprint found in a crime scene. The huge amount of data of the large fingerprint databases (> 30,000,000 fingerprints) seriously compromises the efficiency of the identification task, although the faster minutiae matching algorithms take only a few tens of milliseconds per matching (Wegstein, 1982). If all the fingerprints within a data base were classified a priori, the recognition procedure could be performed more efficiently, since the number of matches would decrease.

Actual IAFISs use *exclusive classification approaches*, i.e. fingerprints are partitioned in some pre-defined distinct classes according to their macro-characteristics. Their performance strongly depends on the number of classes and on the distribution of fingerprints; unfortunately, the number of classes is often small, the fingerprints are non-uniformly distributed (in the most famous classification schemes approximately 90% of fingerprints belong to only three classes) and there are many "ambiguous" fingerprints whose exclusive membership cannot be reliably stated even by human experts. Nevertheless, exclusive classification allows for the efficiency of the ten-print based identification to be improved, since the knowledge of the classes of the ten fingerprints can be used as a code for reducing the number of comparisons at minutiae level. Vice versa, an exclusive classification approach does not

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Fig. 1. The figure shows one fingerprint for each class of the NIST classification scheme; respectively: A = Arch, L = Left Loop, R = Right Loop, S = Scar, T = Tented Arch, W = Whorl.

confer sufficient selectivity to the latent fingerprint searching.

In this work we present a new approach for continuous fingerprint classification; the basic principle is the characterization of the fingerprints with vectors in a multidimensional space. As in many exclusive classification approaches proposed in the literature (Bowen, 1992; Candela et al., 1995; Karu and Jain, 1996; Kamijo, 1993) the macro-characteristics are extracted from the fingerprint *directional image* [3]. The multidimensional vectors are computed by reducing the dimensionality of the directional image through the Karhunen–Loève transform. These vectors can be used for indexing fingerprints through spatial data structures and for retrieving fingerprints by means of spatial queries. Our approach is derived from the method proposed by Candela et al. (1995) at NIST (U.S. National Institute of Standards and Technology), which is, in our opinion, the most promising approach for exclusive classification. We have simulated the latent fingerprint retrieval task both with our continuous approach and with the NIST exclusive one. The results are compared in terms of average retrieval error and average portion of database considered. The results demonstrate the superiority of the continuous approach for the retrieval task.

In Section 2 we briefly describe the foundations of the NIST approach; in Section 3 we introduce our approach for continuous classification. In Section 4 we analyze two different methodologies for latent fingerprint retrieval and, for each one, we formalize the corresponding exclusive and continuous retrieval strategies. In Section 5 we provide the experimental results and finally, in Section 6, we present conclusions and future work.

[3] The fingerprint directional image is a matrix whose elements represent the direction of the tangent to the fingerprint ridge-lines.

2. The NIST approach

The NIST approach (Candela et al., 1995) classifies fingerprints in 6 non-overlapping classes (Fig. 1) by analyzing their directional images.

Before computing the directional images, the fingerprints are *segmented* (i.e. the ridge-line area is separated from the background), and *enhanced*. The computation of the directions is performed by means of the method by Stock and Swonger (1969). The directional image is then *registered* with respect to the core position which is the fingerprint center. The dimensionality of the directional image, considered as a vector of 1680 elements, is reduced to 64 elements by using the *principal components analysis* (KL transform). At this stage a *PNN* (Probabilistic Neural Network) (Specht, 1990) is used for assigning each 64-element vector to one class of the NIST classification scheme. To improve the classification reliability, especially for whorl fingerprints, the authors also implement an auxiliary module (*pseudo-ridge tracer*), which works by analyzing the ridge-line concavity under the core position. Fig. 2 shows

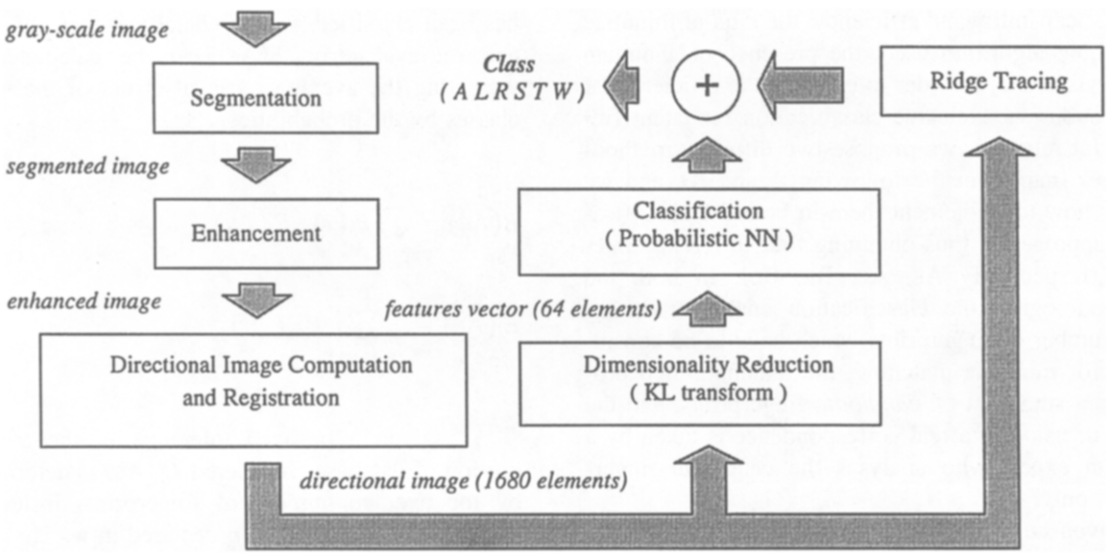

Fig. 2. A functional scheme of the NIST exclusive classification approach.

a functional scheme of the NIST classification approach.

3. A continuous approach for fingerprint classification

In a continuous classification fingerprints are not partitioned in non-overlapping classes, but each fingerprint is characterized with a numerical vector summarizing its main features. Given a "similarity" preserving transformation we can suppose that similar fingerprints are mapped in close points of the multidimensional space considered. This approach enables both the problem of exclusive membership of "ambiguous" fingerprint to be avoided, and the system reliability to be regulated by adjusting the size of the neighborhoods considered.

The feature vectors are extracted from the images as in (Candela et al., 1995); in particular, the directional image is calculated and registered in the same way and each feature vector is computed by using the Karhunen–Loève transform which maps 1680-element vectors in a lower dimensional space [4]. It has been proved (Jain, 1989), (Jolliffe, 1986) that the KL transform guarantees the best Euclidean distance preservation among the unitary transformations for dimensionality reduction. Let $\boldsymbol{u}$ be a directional image and let $\boldsymbol{\Psi}$ be the matrix defining the KL transform [5]; then a feature vector $\boldsymbol{w}$ is calculated as: $\boldsymbol{w} = \boldsymbol{\Psi}^{t} \cdot \boldsymbol{u}$.

If $\boldsymbol{w}$ is the feature vector extracted from a latent fingerprint, we can reasonably believe that its corresponding one $\boldsymbol{w}'$ in the database (if it exists) is sufficiently close to $\boldsymbol{w}$, so that $\boldsymbol{w}'$ can be searched in a hyper-sphere of the multidimensional space with center in $\boldsymbol{w}$.

Persistent spatial data structures (grid file, kdb tree, R tree, etc.) (Samet, 1990) can be used to store and to retrieve data from a large database by using similarity criteria (nearest-neighborhood queries, hyper-spherical range queries, etc.).

4. Strategies for latent fingerprint retrieval

Several strategies for latent fingerprint retrieval can be defined according to the application require-

[4] In our experiments the best results are obtained by using a 5-dimensional space and by linearly re-scaling the elements in the range [0,1].

[5] The matrix $\boldsymbol{\Psi}$ is constituted by the eigenvectors of the covariance matrix defined starting from a representative sample of directional images.

ments: capability and efficiency, the kind of minutiae matching algorithm used, the presence of a human supervisor, etc. In order to evaluate the efficiency of continuous vs exclusive classification for latent fingerprint retrieval, we propose two different methodologies (named in the following A and B), and we show how to implement them in both the classification approaches, thus obtaining four different strategies (respectively AE, AC, BE, BC). In both the methodologies, the classification enables reducing the number of fingerprints which have to be considered for minutiae matching, the matching step produces a small list of *candidate* fingerprints, and the final decision of a real correspondence is taken by a human expert who analyses the candidate fingerprints only.

Given an exclusive classification scheme with s classes, in the following we denote with $P_{\mathrm{d}}(i)$, $i = 1,\ldots,s$ the probability that a database fingerprint belongs to the class i and with $P_{\mathrm{c}}(i)$, $i = 1,\ldots,s$ the probability that a latent fingerprint is assigned to the class i. Please note that P_{d} and P_{c} can be different if the classification method used for the insertion into the database does not coincide with that used for the retrieval.

Methodology A assumes an error-free classification, so the search is restricted to the database fingerprints resembling analogous classification characteristics. The strategy AE can be implemented by searching the whole corresponding class for latent fingerprint; the strategy AC by searching among those fingerprints which are less far from $\boldsymbol{w}$ in the multidimensional space than a prefixed tolerance ρ. The average portion of database considered and the average retrieval error can be formally stated as:

AE: the average portion of database considered $C(\mathrm{AE})$ is:

$$C(\mathrm{AE}) = \sum_{i=1}^{s} P_{\mathrm{c}}(i) \cdot P_{\mathrm{d}}(i),$$

where $P_{\mathrm{d}}(i)$ represents the database fraction involved in the retrieval of a fingerprint of class i and $P_{\mathrm{c}}(i)$ is the weighting factor representing the probability to classify a latent fingerprint as i. Let $P_{\mathrm{d|c}}(j|i)$ be the conditional probability that a database fingerprint, corresponding to a latent fingerprint classified as i, has been classified j in the database; then the average retrieval error $E(\mathrm{AE})$ can be calculated by weighting the average retrieval errors of the single classes by the probabilities $P_{\mathrm{c}}(i)$:

$$E(\mathrm{AE}) = \sum_{i=1}^{s} P_{\mathrm{c}}(i) \cdot E_i(\mathrm{AE}),$$

$$E_i(\mathrm{AE}) = \sum_{j=1, j\neq i}^{s} P_{\mathrm{d|c}}(j|i).$$

AC: given a prefixed tolerance ρ, the average portion of database considered $C_\rho(\mathrm{AC})$ is determined by the average number of fingerprints inside the hyper-sphere with radius ρ centered in $\boldsymbol{w}$. The average retrieval error $E_\rho(\mathrm{AC})$ is determined by the average number of missed retrievals inside the search area.

Methodology B allows for misclassifications to be taken into account; to this aim, the search is carried out incrementally over the whole database, avoiding any possible retrieval error. This methodology requires the search to be terminated when a human expert finds a true correspondence between the latent fingerprint and a database fingerprint that has already been spanned [6]. If the latent fingerprint has no correspondence in the database the search is always extended to the whole database. The strategy BE can be implemented by starting the search from the latent fingerprint class, and incrementally extending it to the other classes; the strategy BE by processing fingerprints according to their distance from $\boldsymbol{w}$, in increasing order.

BE: Let $\boldsymbol{q}^i = \langle q_1^i, q_2^i, \ldots, q_s^i \rangle$ be a permutation defining a class sequence for the retrieval of an i fingerprint. On average, half a class has to be spanned to find the fingerprint corresponding to the latent one, if it exists; and a whole class has to be spanned, otherwise. Therefore, when a correspondence exists

[6] This is reasonable if a human expert works parallel to an IAFIS, analysing step by step the fingerprints which pass the minutiae matching step.

in the database, the average portion of database considered $C(\mathrm{BE})$ is:

$$C(\mathrm{BE}) = \sum_{i=1}^{s} P_{\mathrm{c}}(i) \cdot C_i(\mathrm{BE}),$$

$$C_i(\mathrm{BE}) = \sum_{j=1}^{s} \left(P_{\mathrm{d|c}}\left(q_j^i | i\right) \cdot \left[\frac{1}{2} C_{\mathrm{d}}\left(q_j^i\right) + \sum_{k=1}^{j-1} C_{\mathrm{d}}\left(q_k^i\right) \right] \right),$$

where the term between the square brackets represents the average portion of database considered when the corresponding fingerprint, of an i latent fingerprint, belongs to the jth class (q_j^i); in fact, this term includes the scan of all the fingerprints belonging to the classes which precede q_j^i in $\boldsymbol{q}^i$ and the scan of half the fingerprints belonging to q_j^i. The optimum sequence $\boldsymbol{q}^{*i}$ can be determined according to the following rule. Let a and b be two adjacent classes in the optimum sequence $\boldsymbol{q}^{*i}$, then a precedes b if and only if $P_{\mathrm{d|c}}(b|i) \cdot P_{\mathrm{d}}(a) < P_{\mathrm{d|c}}(a|i) \cdot P_{\mathrm{d}}(b)$; in fact, it can be simply proved that by exchanging the order of a and b the corresponding $C_i(\mathrm{BE})$ values differ only for the above considered terms. Further, the transitive property for the class precedence rule can be proved.

BC: The average portion of database considered $C(\mathrm{BC})$ is determined by the average number of fingerprints inside the hyper-sphere centered in $\boldsymbol{w}$ and with radius ρ given by the distance between $\boldsymbol{w}$ and $\boldsymbol{v}$, where $\boldsymbol{v}$ is the feature vector relative to the database fingerprint corresponding to the searched one.

5. Experimental results

The simulations have been conducted on the NIST Special Database 4 (Watson and Wilson, 1992), containing 4000 (2000 pairs) 256-greylevel fingerprints. The fingerprints are taken from 2000 different fingers, 2 instance (F = first, S = second) per finger. The fingerprints are uniformly distributed in 5 classes (A L R T W). In order to resemble a real distribution (A = 3.7%, L = 33.8%, R = 31.7%, T = 2.9%, W = 27.9%) we reduced the cardinality of the less frequent classes obtaining 1204 pairs. The simulation have been performed by storing the instances F in the database and by retrieving the instances S.

The NIST PCASYS has been used for exclusive classification simulations, producing the confusion matrix reported in Table 1. The ij cell in Table 1 denotes the number of fingerprints whose F instance has been classified i and whose S instance has been classified j; by dividing these values by the total number of pairs (1204) we obtain the joint probabilities $P_{\mathrm{d} \wedge \mathrm{c}}(i \wedge j)$.

From this table we can compute $P_{\mathrm{d}}(i)$ and $P_{\mathrm{c}}(i)$ as marginal probabilities (respectively by summing along the rows and along the columns) and the conditional probabilities $P_{\mathrm{d|c}}(i|j)$ as $P_{\mathrm{d|c}}(i|j) = P_{\mathrm{dc}}(i \wedge j)/P_{\mathrm{c}}(j)$. PCASYS did not classify any fingerprint as Scar, so we cannot estimate the probabilities for this class and consequently the Scar class does not appear in the retrieval sequences. Please note that the above table is quite symmetric and the probabilities $P_{\mathrm{d}}(i)$ do not exactly resemble the real fingerprint distribution, since both the instances are automatically classified. By using these probability estimations we can compute:

- $C(\mathrm{AE}) = 29.12\%$, $E(\mathrm{AE}) = 7.81\%$
- $\boldsymbol{q}^A = \langle A,T,R,L,W \rangle$, $\boldsymbol{q}^L = \langle L,T,A,W,R \rangle$, $\boldsymbol{q}^R = \langle R,A,T,W,L \rangle$, $\boldsymbol{q}^T = \langle T,A,L,R,W \rangle$, $\boldsymbol{q}^W = \langle W,L,R,T,A \rangle$, $C(\mathrm{BE}) = 17.16\%$

As far as continuous classification is concerned, we have implemented our continuous approach by using a grid file (Nievergelt et al., 1984) for storing and retrieving fingerprints. The graph in Fig. 3 shows the average retrieval error $E_\rho(\mathrm{AC})$ and the average portion of database considered $C_\rho(\mathrm{AC})$ as a function of the tolerance ρ. The graph in Fig. 4 summarizes

Table 1
Confusion matrix produced by PCASYS

Instance F	Instance S					
	A	L	R	S	T	W
A	60	15	10	0	3	0
L	12	376	2	0	1	8
R	12	6	369	0	0	4
S	0	0	0	0	0	0
T	2	4	1	0	2	0
W	1	7	6	0	0	303

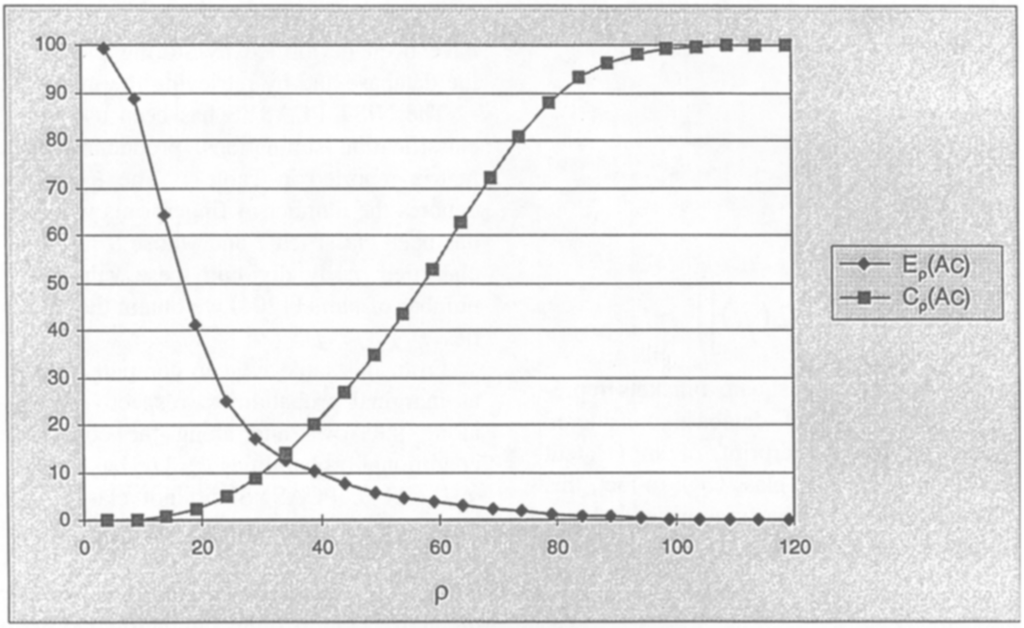

Fig. 3. $E_\rho(\mathrm{AC})$ and $C_\rho(\mathrm{AC})$ as function of ρ.

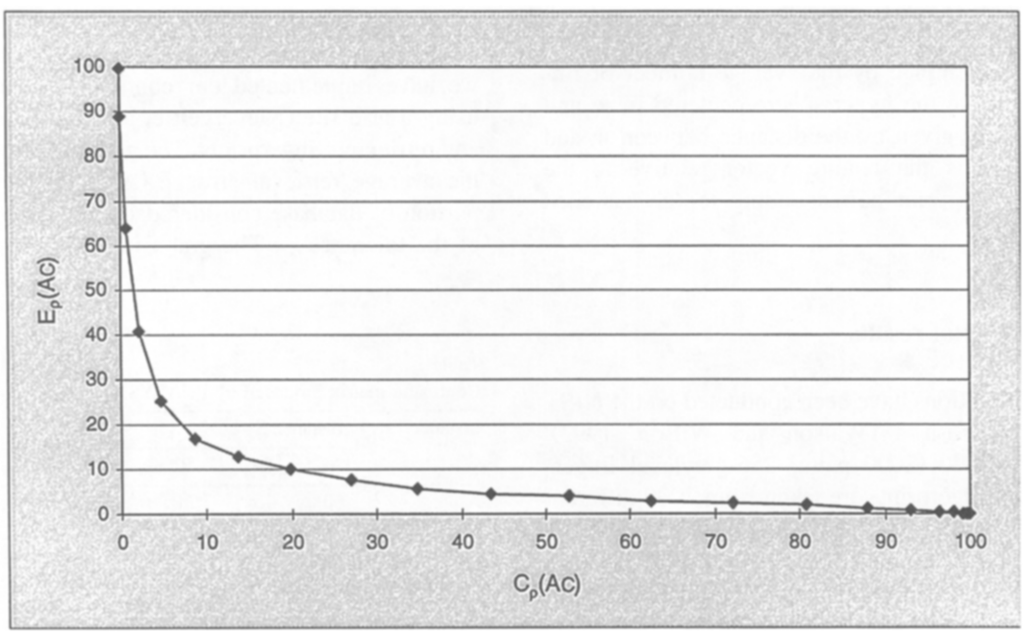

Fig. 4. The graph shows pairs $E_\rho(\mathrm{AC})$, $C_\rho(\mathrm{AC})$ relative to the same ρ.

the above data by plotting the pairs $E_\rho(\text{A}_\text{C})$, $C_\rho(\text{A}_\text{C})$ relative to the same ρ.

$C(\text{B}_\text{C})$ has been experimentally determined by counting for each instance S how many instances F are closer to S than its corresponding fingerprint, and by averaging the results.

- $C(\text{B}_\text{C}) = 6.90\%$

All the simulations in A_C and B_C have been carried out by reducing the space dimensionality to 5, which has been proved to be the best solution in our experiments. Therefore we argue that only the first few eigenvectors contain useful information for a good fingerprint characterization; in fact, by including further eigenvectors we deteriorate the system performances due to the presence of noise and small perturbations in the lower module eigenvectors.

As far as methodology A is concerned, the results show that slightly better performances can be obtained, in terms of the average percentage of database searched ($C_{\rho'}(\text{A}_\text{C}) = 26.23\%$, $C(\text{A}_\text{E}) = 29.12\%$), with the continuous classification approach, at the same average retrieval error ($E_{\rho'}(\text{A}_\text{C}) = E(\text{A}_\text{E}) = 7.81\%$), $\rho' = 43.51$. Furthermore, in a continuous classification approach, we can define the reliability level a priori by tuning ρ (increasing the time spent for retrieval to decrease the average retrieval error). As concerns methodology B the results show that strongly better performances can be obtained, in terms of the average percentage of database searched ($C(\text{B}_\text{C}) = 6.90\%$, $C(\text{B}_\text{E}) = 17.16\%$), with the continuous classification approach.

In this section our continuous approach has been compared against the NIST exclusive one in terms of average retrieval error and average portion of database considered. Now, we conclude our discussion by briefly addressing the time complexity of the feature extraction and the amount of extra-storage required by the data structure used for indexing fingerprints. Feature extraction requires a time slightly lower than the NIST approach (7 seconds on a DEC Alpha Workstation) since it does not include the last two steps. The extra-storage required by the index can be determined as follows: for each fingerprint a couple $\langle w, p \rangle$ must be stored, where w is the fingerprint feature vector and p is a pointer to the fingerprint record; these couples must be stored into a multidimensional structure which requires an amount of storage typically 1.5 times greater than the space needed for a sequential arrangement. Since a fingerprint record (which usually contains the image, the minutiae list and other alphanumeric information) is many orders of magnitude larger than an index couple, the extra-storage required by the index can be neglected.

6. Conclusions

In this work we have compared two different approaches for fingerprint classification and evaluated their capability for latent fingerprint retrieval in large databases. Two different methodologies for latent fingerprint retrieval have been considered and implemented both with an exclusive and continuous classification. The results obtained show that better performance can be achieved, in both the methodologies, through the continuous approach.

A remark is in order: the aim of this work is not to prove the superiority of our approach with respect to other exclusive classification approaches. In fact, continuous classification does not enable to accomplish some tasks to be carried out, such as fingerprint labeling according to a given classification scheme. Nevertheless, if we classify fingerprints only for improving the retrieval efficiency, our continuous approach is more suitable than classical exclusive ones.

As far as future research is concerned, we are working for further improving the performance of our classification system. From the analysis of experimental errors (strategy A_C) it is clear that the main errors are due to noise, translation and rotation of the fingerprints. NIST Special Database 4 includes some very low-quality fingerprints (as occurs in some real latent cases) which sometimes cause errors in strategy A_C and make inefficient strategy B_C. In order to overcome these problems we are developing a new continuous approach based on the characterization of the directional images by relational graphs which are invariant with respect to translation and rotation (Maio and Maltoni, 1996). Finally, some investigation is necessary in the field of spatial data structures for storing a large amount of data and for efficiently retrieving them through complex spatial queries.

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