Rapid and Reliable Content Based Image Retrieval

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Abstract. The paper concerns an open problem in the area of Content Based Image Retrieval (CBIR). A new constructive method is proposed for an effective CBIR indexing, either a fast or noise tolerant one as well as well suitable to the conventional Database (DB) specifics of Images' keeping (IDB). The method's consistency is proved by analysis of both the most spread viewpoints on CBIR, the IDB viewpoint and the computer vision one. Different techniques based on the method are briefly described and results of their real tests by an Experimental Image Retrieval System are also committed.

Keywords. Content Based Image Retrieval (CBIR), Image DB (IDB), fast and noise tolerant CBIR.

Introduction

Content Based Image Retrieval (CBIR) is a relatively new area of Informatics that covers techniques for automatic (or automated) retrieval of image and/or video objects by features (e.g., color, texture, shape, movement, etc). The current CBIR is often qualified as being in the "early" stage, because of the predominantly simple statistics (histograms) of these features considered. However, these simple statistics are usually preferred to more sophisticated structures like contours, trajectories, etc., because of the well-known difficulties encountered by segmentation of graphical objects, even in cases of low levels of image noise [1, 2, 3].

There are known CBIR systems in world practice, such as TRADEMARK (1992), QBIC (1993), Virage (1995), Photobook (1997), ARTISAN (1999), PictureFinder (2002), etc., but most of these can only be associated with this "early" CBIR. Similarly, while a large number of image databases (IDBs) are available on the Internet, they also need the proper retrieval tools [4, 5, 6].

An ordinal CBIR system includes a multimedia database (IDB) for keeping images and/or video data and for maintaining typical user queries, a graphical user interface to request wording and visualization results, and suitable indexing techniques for feature vector storing as well. These indexing techniques are currently being intensively researched to find an effective method for either fast or noise tolerant CBIR.

The paper proposes a new constructive method for an effective CBIR indexing well suited to conventional DB specifics. This method's consistency has been proved (Section 1.3), analyzing both the most widespread viewpoints on CBIR, DB (Section 1.1) and image processing and recognition (Section1.2). Three techniques are considered for method realization (Section 2): image contour analysis, image wavelet analysis, and image Fourier analysis. The techniques are briefly described from a speed (fast retrieval) perspective (Sections 2.2 and 2.3) and from a noise tolerance interpretation (Section 2.4). The techniques have been tested (Section 3) on both aspects of interest – performance speed and noise tolerance, via the so-called Experimental Image Retrieval System (EIRS) operating on test IDBs, consisting of approximately 4000÷14000 hallmark images.

1. Basic Formulation

The most general peculiarity of CBIR systems is that they are usually developed based on conventional DB Management Systems (DBMS), resulting in their inheriting all the DBMS advantages and shortcomings. The DBMS methods for fast (indexed) data access are generally optimized for textual and numerical data, and are inappropriate for other types of objects, e.g. images and/or video. The well known extensions of these methods, e.g., *R*-trees, *k*-D trees, etc. [1, 4, 5], were generally developed for the so-called GIS (Geographic Information Systems) technologies, which is why they do not directly meet CBIR specifics. More sophisticated CBIR approaches, borrowed from pattern recognition areas, generally lead to a so-called sequential access to images from the IDB, which is also unacceptable, especially in cases of large IDBs.

Another popular approach to speed up CBIR (from a DB viewpoint) is to pre-annotate the IDB, via a structure of textual descriptors (keys), e.g., following the so-called Vienna convention, well known in patent offices’ practice. The approach is simple but also inappropriate, because it requires user-operator’s involvement, which either slows down the effectiveness of retrieval, or, in the case of large IDBs, prevents it. Nevertheless, this interactive DB support approach is definitely promising for future CBIR systems that will search by logical and/or abstract queries. For instance, recent research [7] proposes a pre-annotation approach, not to the whole IDB but to a portion of it (~1%). Definite CBIR hopes are also linked to machine learning approaches, for both short and long term learning [3]. Finally, classical computer vision approaches to CBIR should also be mentioned [1, 2, 3, 4].

Actually, CBIR should be considered from at least four viewpoints [1], namely:

- Computer Vision (CV), and more precisely Image Analysis and Pattern Recognition (IAPR);
- Databases (DB) and DB Management Systems (DBMS);
- Artificial Intelligence (AI) and especially Machine Learning (ML), and knowledge DBs as well;
- Graphical User Interfaces (GUIs) as well as multimodal UI in CBIR that aid the human-operator.

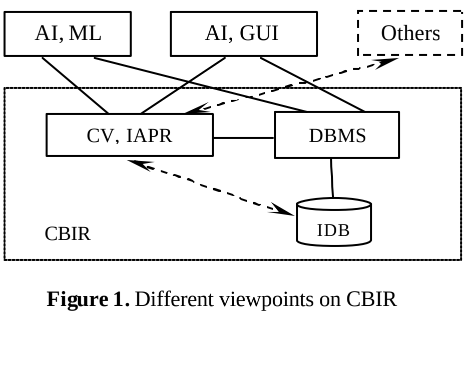

Figure 1. Different viewpoints on CBIR

This paper has been limited to the first two viewpoints, considered by the following “formulae”:

$$\text{CBIR} = \text{IAPR} + \text{IDB}\,, \qquad (1)$$

i.e., CBIR will be discussed as an interdisciplinary area between IAPR and IDB, see also Figure 1.

1.1. DB &DBMS Viewpoint on CBIR

Given relational table for IDB description, see Figure 2, can be represented as:

$$((\, i,\ a_1^{(i)},\ a_2^{(i)},\dots,a_k^{(i)},b_1^{(i)},\dots,b_{n-k}^{(i)}\,),\ 1\le i\le N) \equiv$$
$$\equiv (\ (\mathrm{ID}) \Diamond (A_1) \Diamond (A_2) \Diamond \dots \Diamond (A_k) \Diamond (B_1) \Diamond \dots \Diamond (B_{n-k})\,)\,, \qquad (2)$$

where i is the record identification code (ID), and N=|IDB|. On the left (top) side of the above equation is the rows' interpretation and on the right (bottom), the symbols ◊ show the column's interpretation (i.e. same name features). The columns are split into two groups, {a} and {b}, and can be interpreted as:

- informative {a} and unessential {b} features (from an IAPR viewpoint), or
- coordinates {a} of k-dimensional (k-D) feature space, and (n-k)-dimensional vector objects {b} therein, $n>k$, (from another viewpoint of IAPR), or
- primary {a} and secondary {b} keys (from a DB viewpoint), or
- key {a} fields (primary and/or secondary ones) and ordinary {b} fields for extra information, etc.

For instance, the so-called BLOB fields [8], where IDBs usually keep images, can be considered {b} type.

Both basic types of DB access methods of interest are hereinafter referred to as Sequential Access Methods (SAMs) and Index Access Methods (IAMs).

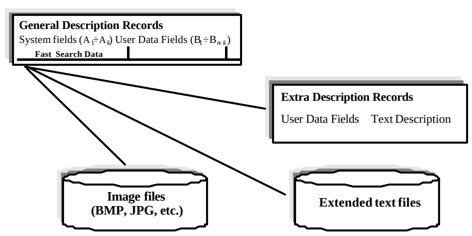

Figure 2. A simplified logical scheme of IDB for CBIR

SAMs are restricted by the so-called Peano principle, i.e., given record (j) could be read if, and only if, the preceding record (j-1), $2\le j\le N$, is already read, i.e., the average access time is $\sim O(N)$, N=|DB|.

IAMs ensure much faster access time $\sim O(\log N)$, and can be performed on each field of both {a} and/or {b} types. To do this, a linear order over the chosen field should be defined. In DBMS terms, this means constructing a separate index file for this field, also called a *key field*. Each field A (or B) of the table, see Eq.2, takes a symbolic value, so that it can always realize a key, via the natural order S over these values:

$$\overline{j} = S(a^{(j)})\,,\ 1\le j< N\ ,\ a^{(\overline{j})} \le a^{(\overline{j}+1)}\ ,\ a^{(\cdot)}\in A\ . \qquad (3)$$

Briefly, using the order S, the DBMS index on the field A returns a pointer (the ID) to that object of DB, whose feature value is respectively the greatest one less (or at least equal) to the given (input) value a.

1.2. CBIR from an IAPR Viewpoint

Most commonly, when an image I is input in an IAPR system, then the output O is expected to be informative enough for the *class C* to affiliate the image, see Figure 3.

The classes C_m, m=1,2,…M that the system has to recognize are often considered non-crossing subsets of the so-called *world* ***C*** of the system:

$$C_m \cap C_n = \varnothing\ ,\ C_m \in \boldsymbol{C}\ ,\ C_n \in \boldsymbol{C}\ ,\quad \boldsymbol{C} = \bigcup_{m=1\div M} C_m \quad , \tag{4}$$

and the recognition algorithm can be expressed by the following test sequence:

$$m := 1\ \Rightarrow\ (I)R(C_m) = \begin{cases} \text{false}\ \Rightarrow\ m := m+1 \Rightarrow\ (I)R(C_m) \\ \ \text{true}\ \ \Rightarrow\ O := m\quad \Rightarrow\ \text{end} \end{cases} \quad , \tag{5}$$

where (.)R(.) is a correspondence relation based on our confidence that $I \in C_m$ or $I \notin C_m$, m=1÷M.

Usually, the (I)R(C) test is difficult to perform directly because of a possible variety of objects, which is why this relation is properly extended to a triple relation of similarity S(A, B, s), where A and B are two arbitrary objects from the world ***C***, and s is their degree (measure) of similarity. Most often, the relation S is represented by a *similarity function S*:

$$s = S(A, B)\ ,\ A \in \boldsymbol{C}\ \ ,\ B \in \boldsymbol{C}\ \ ,\ s \in\ (0 \div 1]\ , \tag{6}$$

perhaps defined for a part of ***C*** only. Thus, the (I)R(C) test can be set up as:

$$(I)R(C_m) = \text{true}\ \ \Leftrightarrow\ \ \forall(n \neq m)(\,s(I, A) \leq s(I, B)\ ,\ A \in C_n\ \ ,\ B \in C_m) \tag{7}$$

which is enough to describe many of the well known IAPR methods, e.g., the Nearest Neighbor (NN) method, the k-NN one, etc., [9].

The definition of the appropriate function S for a concrete application (world ***C***) is a currently open problem of IAPR. Several approximations are usually admissible, e.g., the potential function's method known in nonlinear discriminate analysis. Using a *metrics* in the world ***C*** or at least a *distance function* defined only for the important object couples therein is also very popular.

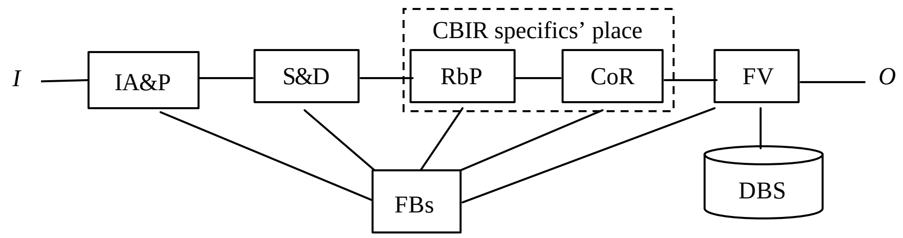

Figure 3. A general IAPR interpretation of CBIR, where: (IA&P) = Image Acquisition & Preprocessing, (S&D) = Segmentation & Decomposition, (RbP) = Recognition by Parts, (CoR) = Composition of Result, (FV) = Final Verification, with a DB of Standards (Examples), and (FBs) = possible Feedbacks.

To perform the correspondence and/or similarity tests, the input image information is necessary. Two basic approaches are used for that, namely:

- Vector representation of I, $I \sim (x_1, x_2, \ldots x_k)$, as a fixed feature string of length k, where the values x_i of each feature, $i=1 \div k$, can be measured (evaluated).
- Structural representation of I, $I \sim H=(V,E,\ldots)$, where the structure H can be generally considered as a graph, with V, the set of vertices, E the set of edges among them, and with respective attribute values over V and E, and so on.

Without loss of generality, we can restrict ourselves to vector representation only, which naturally leads to a representation of the world $\boldsymbol{C}$ as a *linear vector space* $\boldsymbol{C}$ *of features*:

$$\boldsymbol{C} \equiv \{ X \mid X = (x_1, x_2, \ldots x_k) \} \quad , \tag{8}$$

with k the number of dimensions (features), and where each object X is represented as a point (k-D vector). Thus, we reach the often used *Euclidean distance* (also a metrics):

$$D(A,B) = \| A - B \|, \ \| X = (x_1, x_2, \ldots x_k) \| = (x_1^2 + x_2^2 + \ldots + x_k^2)^{1/2} \ , A \in \boldsymbol{C},\ B \in \boldsymbol{C},\ X \in \boldsymbol{C} \ . \tag{9}$$

Ignoring certain details, we can assume that the chosen k features representing the world $\boldsymbol{C}$ are informative enough, and that they can be ordered by importance, for definiteness, in descending order. Because of the CBIR context, we consider only objects belonging to the world of images.

1.3. Correspondence between Both Basic Viewpoints

In this way, the Eq.(1) formulation of CBIR assumes the following more concrete sense:

- CBIR inherits most of the IAPR methods, assuming that the preliminary knowledge for the solved task is stored in an IDB. The IAPR space of features, Eq.(8), corresponds to the relational table description of IDB, see Eq.(2).
- The solved tasks (from a DB viewpoint) are: (i) search by example, and (ii) search by group of examples (category search). They correspond (from an IAPR viewpoint) to: (j) identification (recognition) of an object and (jj) objects' recognition (association with class).

Each key (IDB table column) consists of key fields, each with a fixed length, L, that may vary for different keys. These fields, where number N equals the number of records (DB table rows), store number values, textual strings, and/or Boolean values.

From an IAPR viewpoint, a key is primarily a one-dimensional (1D) array F, of a length N=|DB|, whose values are of a fixed precision respecting L.

If given key (i.e., DB object feature) is a primary one, then each of its values $x(j)$, $j=1 \div N$, corresponds to a *unique* (the j-th) object in the DB. If the key is a secondary one, then its given value v may correspond to a *group of objects* $\{j_1, j_2, \ldots j_m\}$, with m being its number, i.e., $x(j_1)= x(j_2)=\ldots= x(j_m) = v$.

To effectively use a given conventional DB, i.e., to build a plausible CBIR index, it is necessary that the space $\boldsymbol{C}$ objects be orderable into a full order of the Eq.(3) type.

Formally, this is assured by the described correspondence: ⟨feature space ⟩ ⇔ ⟨DB table⟩; nevertheless, the practice requires also IAPR specific experience.

The task for association with an object class is general for the IAPR area. Usually, decision methods lead, as already mentioned, to similarity function *S* and, in particular, to distance function *D* among the object pairs. Thus, even being defined for the whole ***C***, either *S* or *D* leads, in general, only to a partial order of objects (see Figure 4a), while the index definition needs a full (linear) order relation (see Figure 4b).

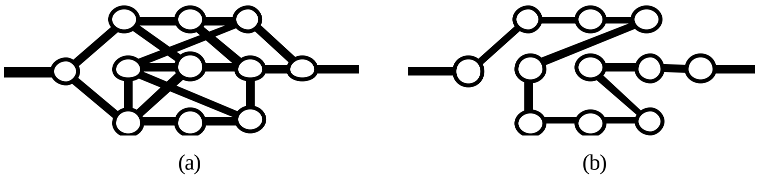

Figure 4. A similarity graph defining: (a) a partial order, and (b) a full (linear) order in the object world

Therefore it follows the main idea (*hypothesis*) of this paper, namely that:
A possible (and promising) approach to an effective CBIR is to cut off the partial order defined by given similarity function over the feature space, in such a way that a full (linear) order relation can be obtained, which will be enough for an appropriate DB index to be built.

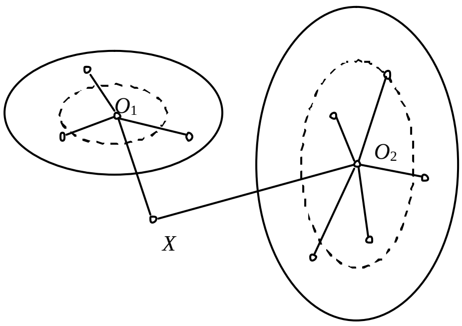

Figure 5. Two areas of Mehalanobis distances defined for the objects therein. The full order is obviously impossible.

1.4. Illustrative Examples

It is not very difficult to show that the similarity *S*, see Eq.6, (or the distance *D*, see Eq.9) is only going to appear as a full order in the world ***C*** in some particular cases. It is enough to remember that both *S* and *D* are symmetrical two-place relations, while the order relation, whether a full or partial one, is anti-symmetric by definition. In other words:

(i) *If a metrics is defined* for the set ***C***, e.g., by Eq.9, then these metrics cannot be directly applied to obtain a full order, except when the "*triangle inequality*" from the metrics definition degenerates into an equality, for instance, in the 1D case (for k=1). Thus, to define a key, respecting the given metrics, it is necessary to appropriately "cut off" the full "graph of distances". From the combinatorial large number of opportunities, we have to vote for only one, the key we need. This approach to ordering, object by object, is often called "*scanning*" of the space ***C***, e.g., *R*-trees in a 2D-***C*** [5]. Here we primarily consider scanning by coordinates (i.e., features), to order them by importance, also known as hyper-rectangles' trees [1].

(ii) *If the available distance is not a metrics*, then it is very possible that an appropriate cut-off does not exist. The so-called Mehalanobis distance [9] is an example of this, see also Figure 5.

2. A Promising Approach to the "Rapid and Reliable CBIR" Problem

2.1. About the Images of Interest

Graphic images, which will be the main focus hereinafter, can be considered to be reproduced by a small number of colors or half tones (i.e., gray intensities), whose respective areas are of a sufficient size. Ideally, these images should be centered, i.e., the essential graphics should be in the "middle" of the image frame, while the area near the frame should be filled only with background color (or half tones). Graphic images are intensively used in patent office activities, e.g. for registration of companies, firms, etc., and are popular by the names "hallmarks", "trademarks", or simply "marks" [10, 11], see also Figure 6.

(a) (b) (c)

Figure 6. Three examples: (a) a halftone (gray) image, (b) almost B/W one, and (c) colors converted to gray

Depending on the success with a chosen type of image, the results obtained could, without difficulty, be spread over a larger spectrum of images using the "split and own" principle. This is very popular in the IAPR area, see also the module couple, (RbP) and (CoR), in Figure 3.

2.2. Three CBIR Techniques for Fast IDB Access

Keeping in mind the cut-off idea, see Section 1.3, three *techniques* for image key derivation have been proposed considering both the CBIR necessities and the conventional DBMS limitations:

(**T1**): a heuristic decomposition of images to contextual contour parts, cf. [12, 13],

(**T2**): a two-dimensional wavelet transform, cf. [14], and

(**T3**): a two-dimensional Fourier transform and heuristic modifications, cf. [15].

Although applying different recognition principles (and/or feature spaces), the above three techniques are built on the following common statements [13, 15]:

- The search content is the input image itself or a sketch of it.
- The most essential image data are automatically extracted and arranged in a key string of a fixed length (following the chosen technique – **T1**, **T2**, or **T3**).
- The fast access is performed using conventional IAMs of the given DBMS.
- Noise tolerance is treated the same way by each technique, i.e., in parallel with the processing speed characteristic for the basic IAM applied.

The techniques proposed are illustrated in Figures 7 and 8 on the example of Figure 6a.

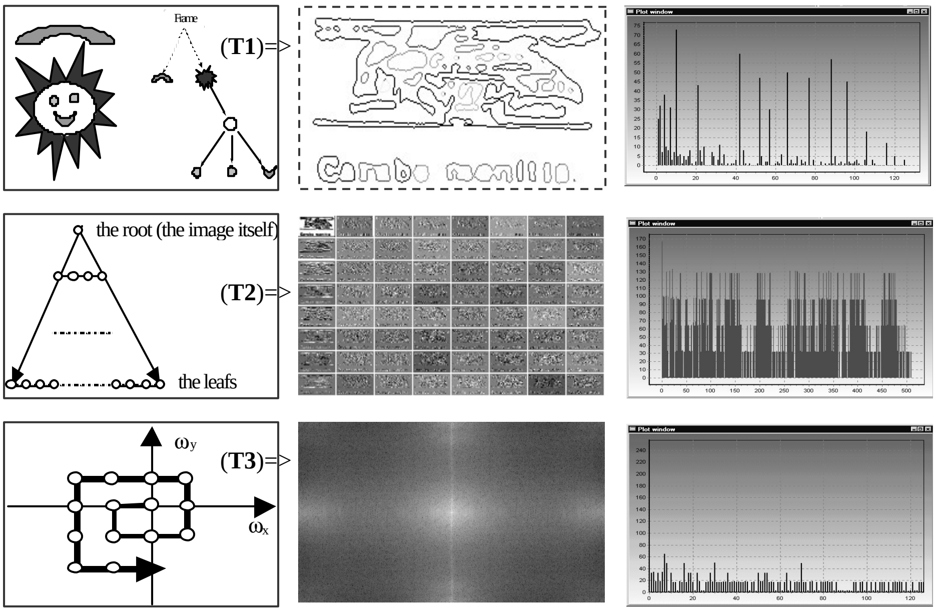

Figure 7. Feature space scanning and IDB keys derivation by the three techniques proposed

No decomposition of input image is applied, in the sense of Figure 3. The final IDB verification is performed based on the image key, i.e., a lossy-compressed but informative enough representation of the image, reflecting given user perception for the image context importance. Specific problems connected with a technique's invariance against accidental rotation, scaling and/or translation of the images are solved according to each technique's specifics.

2.3. Proposed Techniques Combination

The **T1** technique is rotationally invariant by definition (because of 1D FT applied) but is sensible to noise, while **T2/T3** have quite opposite characteristics. Thus, attempts to improve the proposed method have been focused on **T3** modifications as follows:

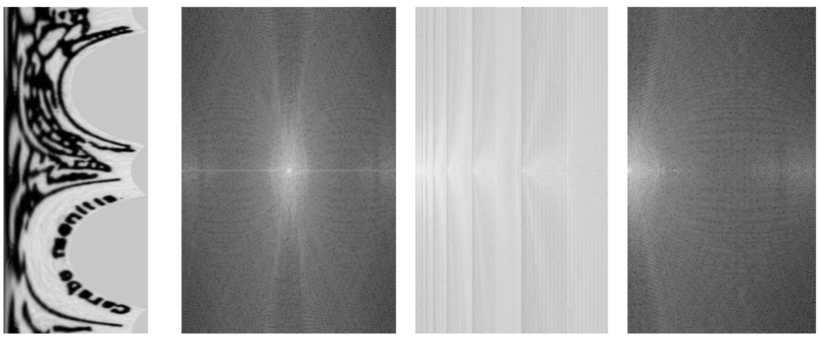

Figure 8. Modifications of the **T3** technique: **T3a**, **T3b** and **T3c**, after a preliminary Simple Polar Mapping

(**T3a**): applies a simple polar Mapping of the input *I* before its 2DFT, cf. [15, 16],

(**T3b**): similar to **T3a:** vertical 1DFT and horizontal 1DWT instead of 2DFT, [15],

(**T3c**): similar to **T3b:** a 1D CosFT, [17], is used horizontally instead of 1DWT.

These modifications are illustrated in Figure 8 on the same "ant" image of Figure 6a.

2.4. Noise Tolerance Interpretation

Given object $X=(x_1, x_2, \ldots x_k)$ of the feature space $\boldsymbol{C}$ can be considered an *error version* of another object $F=(f_1, f_2, \ldots f_k)$, by the formulae:

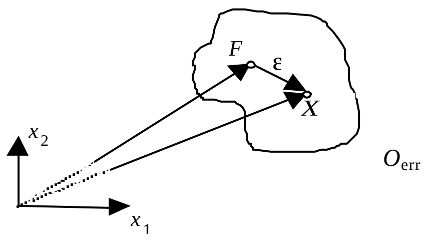

Figure 9. Errors' model in the feature space

$$X = F + e\ ,\ \ e = (e_1, e_2, \ldots e_k)\,, e \in \boldsymbol{C}\,, \tag{10}$$

where the vector $\boldsymbol{e}$ is usually called the *error vector.* One object (e.g., X) could be interpreted as the input object (for recognition), while the other, F, as an object already stored in the IDB. This doesn't depend on the facts of where and when the error occurred! A 2D illustration is given on Figure 9.

If the space $\boldsymbol{C}$ metrics is defined, then the error rate can be evaluated by the norm (module) of e:

$$\|e\| = (e_1^2 + e_2^2 + \ldots + e_k^2)^{1/2}\ ,\ e \in \boldsymbol{C}\ \ . \tag{11}$$

On the other hand, it is most often statistically considered that the error probability diminishes polynomially (or even exponentially) if the distance $\|e\|$ to the centre F increases. Thus, we arrive at the definition of *error domain* O_{err}, $F \in O_{\text{err}} \subset \boldsymbol{C}$, and even – the *domain of most probable errors*. For one-modal error probability densities, these domains often occur one-fold and as convex ones, by Gaussian densities, they occur as hyper-ellipses, or even spheres – uniformly distributed on the separate coordinates of $\boldsymbol{C}$. A well known rule for the noise suppression (by the distance minimum to the original vector F) can be written as:

$$D(F, F+e) \le d_{\min} = \tfrac{1}{2}\min\{D(A,B)\,|\,A, B \in \mathbf{E}^n \equiv \boldsymbol{C}\}\,,\ F \in \boldsymbol{C}\,, e \in \boldsymbol{C}\ . \tag{12}$$

For index conformity, error domains are most often considered rectangular and parallel to respective coordinate axes, i.e., hyper-rectangles.

One more popular IAPR approach, which can be interpreted as the noise tolerance aspect, is feature space squeezing, or, more precisely – reducing of the space's dimensions number k, e.g. using Karunnen-Loeve's approach of principle components.

Both above approaches are exploited by the techniques (**T1**, **T2** and **T3 a,b,c**), i.e.:

• For given key of IDB, the coordinate axes of $\boldsymbol{C}$ are ordered (*enumerated*) by their importance. The enumeration should be preliminarily defined, possibly by intuitive rules complying with user preferences.

• Error domains are interpreted by *tolerances* for the generated keys and represent hyper-rectangles.

The above description reflects the so-called "*regular noise*" problem.

The real image experiments encountered another problem, which we call the "*rough artifacts' noise*" problem. A similar noise example is given in Figure 6b, where noisy artifacts surround the mark situated in the middle (a piece of newspaper appears under the mark). The approaches necessary to mitigate against rough noise lie beyond this paper.

3. The Experimental Image Retrieval System

A software system, which we call EIRS (Experimental Image Retrieval System), has been designed to support experiments with the proposed method for Rapid and Reliable CBIR [18].

Considering its possible application area, EIRS remains perhaps the closest to the system ARTISAN, which was designed for the Royal Patent Office necessities [19]. ARTISAN searches for mark images, generally accenting the more common shapes (line-cuts, circle-cuts, ellipses, etc.) as well as their relations (parallelism, closeness, etc.). EIRS primarily searches by arbitrary image examples, generally focusing on processing speed and noise tolerance.

At the time an instrumental software, EIRS allows testing the above mentioned techniques (**T1**, **T2** and **T3a,b,c**) concurrently, on test IDBs consisting of 4000÷14000 images. The retrieval time per image is about a few seconds (3÷5s), mostly depending on the access time of the HDD used. The average error rate for regular image noise (produced by accidental linear transforms of image acquisition) is about 2%, i.e., by arbitrary introduced noise, less than 2% of IDB images do not succeed in winning the first position in the similarity list of the respective retrieval experiment. EIRS is written in C++ and operates in a Windows 98/NT/XP environment, on IBM PC compatibles.

4. Conclusion

The paper proposes and proves the consistency of a universal CBIR superstructure over the index access methods of a conventional DB&DBMS used for image storage. This superstructure, which we call "rapid and reliable CBIR", respects user requirements for either processing speed or noise tolerance. From a computer vision viewpoint, this superstructure can be interpreted as a specific technology for image recognition backed by an after the fact verification with a glossary, a DB of image examples.

It is assumed that the proposed method is not limited to images, but can also be applied to 1D objects (e.g., sounds, music, speech), a time series of images (video-clips or short-movies) and/or multimedia. There are no limitations concerning the volume of the respective DB and/or its location, locally or via Internet.

The main limitation of this method, namely the "object against background", is currently being investigated as to whether it can be reduced, which, if successful, would enlarge the method's possible applications. Definite hopes in this respect are connected with a near future combination of the techniques proposed, namely between

T1 as image context decomposition by respective sub-object contours and **T2**/**T3** as more resistant ones to a larger spectrum of image noise.

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