Geometric-Morphological Method for Artifact Noise Isolation in the Image Periphery by a Contour Evolution Tree

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Abstract: *This paper presents an original method for noise-filtering of the like of image peripheral artifacts, by defining a Contour Evolution Tree (CET). CET is defined by classical morphological techniques, but to achieve efficiency, the latter are generally presented by the well known distance transformation for images. The method aims, but is not limited to, improving the noise tolerance of content based image retrieval in a database of trademark images.*

Keywords: *Image processing, Image morphology, Contour Evolution Tree (CET), Distance Transform, Noise-artifacts, Content based image retrieval (CBIR).*

INTRODUCTION

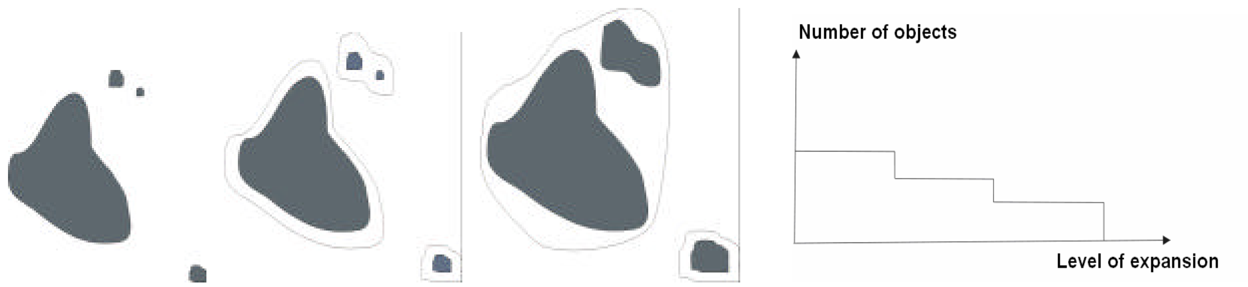
Noise filtering (reduction) in images is a classical and prevailing task in the subject of Image processing and recognition [5, 6, 8]. Particularly, this problem is tackled when dealing with systems, administering Image Databases (IDB), where the so called CBIR (Content Based Image Retrieval) methods for data access have lately been applied. The CBIR access method acts as follows: it extracts the essential content from an initial image and uses it to organize the search for similar images in the IDB. Except for speed, the CBIR method needs to provide a certain level of noise resistance, at least as far as the standard noise, which is typical for the process of image retrieval. Such a system example is EFIRS (Effective and Fast Image Retrieval System), which is being developed at the Bulgarian Academy of Sciences (BAS) for the needs of the Patent Office of Republic of Bulgaria (PORB), and specifically for their vast IDBs of trademark images [3, 4].

However, except for standard noise, the images at PORB often contain a particular noise of type "artifacts in the image periphery." The existence of this *artifact-noise* reduces dramatically the CBIR efficiency and, in particular, the EFIRS efficiency.

This article proposes an original method to isolate/suppress artifact-noise in images. Its main idea is listed below in Section 1. Section 2 describes the initial limitations, as well as the applied theoretical base. The crux of the described method, the Contour Evolution Tree (CET) is illustrated in Sections 3 and 4. A detailed description of our test experiment is listed in Section 5.

1. MAIN CONCEPT OF THE PROPOSED METHOD

The method targets black-and-white images in positive, that is – black objects (the key objects and noise objects) on a white background. The premise is that the key object (or group of objects) is mainly located around the center of the image, while the non-essential objects (or noise-artifacts) are to be found in its periphery.



(a) (b)

Fig.1. Sequence of expansion (grouping) of image objects: a) results by two stages of expansion, and b) the grouped objects number depends monotonically on the expansion.

The method's idea is in the consecutive and gradual expansion of the separate (disconnected) objects in the image, in observing the process of their grouping and in defining the stopping rule by reaching the situation – one grouped object and one grouped noise-artifact on a white background (see Fig.1a, the 3rd picture there).

To formalize the process of expansion and grouping, we are defining the above-mentioned CET. CET describes the process reversibly and uniformly. Every level of the CET reflects one expansion action, for example: dilation by a radial-isotropic structural element of a "singular" area. The nodes of the CET represent the grouped objects and/or artifacts at a given expansion stage (level). Further weight coefficients are defined in the CET nodes in order to identify more precisely the noise segmentation process. To improve the overall processing speed we substitute the series of morphological expansions by a *Distance Transform* (DT), implemented only one time over the entire image [2] (see Fig.2a). This substitution is reasoned on the almost evident fact that as the level of expansion grows, the number of grouped objects decreases monotonically (Fig.1b), which allows for a faster CET construction over the DT-map of the given image.

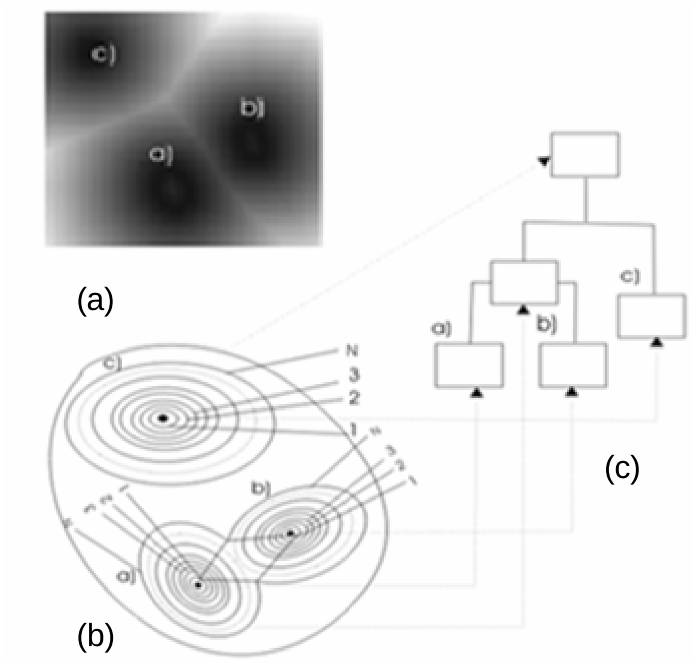


Fig.2. The expansion process, depicted by DT and CET over an image of 3 objects (simple points): a) DT 5-7-11 of the image, b) object shapes over the sequence of expansion, and c) the resulting CET of the image.

2. PREMISES OF THE TASK

The images under observation abide by the following considerations (also called a priori information [8]):

Consideration 1: The input image is in binary form and contains black objects on white background.

Consideration 2: The key content (the objects) of the image is predominantly located in/around its center.

Consideration 3: The rough 'artifact' noise is located mainly in the image periphery.

Consideration 4: The key objects and noise-artifacts are analyzed as groups of geometrically-distinguishable entities, we call them *black shapes*, or simply *shapes*.

Thus, we are looking for a geometrically-morphological method for isolating (and/or suppressing) of noise-artifacts in trademark images. Examples of trademark images (or *trademarks* in brief) are listed in Table 2 below.

2.1. Criteria to localize a noise-artifact.

To intuitively segment the noise-artifact in a trademark image, we introduce the following two criteria:

Criterion 1: The bigger the number of shapes, which are located close to one another, the higher is the certainty that they are *objects*, as opposed to the rest of *artifacts*. Reversely, the further away a shape is from the others, the more we consider it as noise-artifact.

Criterion 2: The closer a group of shapes by Criterion 1 to a major cluster, the bigger is the confidence that both the group and the cluster are *objects*. The basis for this criterion is the possibility that a *group of artifacts* can form a tightly connected group (by proximity) and in this way to be misrecognized as relevant objects.

2.2. Description of a series of expansions via a DT-map of the image.

Following the main idea, at every expansion stage of the given shapes**,** we can use the morphological process of *dilation* $\oplus$ via a band of single width:

$$X \oplus B = \{ p \in e^2 : p = x + b, x \in X, b \in B \} \qquad (1)$$

where according [8] we define: e^2 is the original image, analyzed as a set of pixels (black or white); X is any of the shapes, which we want to expand ($X \subseteq e^2$); and B is the structural element of the given *dilation*. For an isotropic (equal in all directions) and minimal (but not empty) expansion of X, we pick B as a 3x3 mask filled with black pixels only, and with basis in its center.

For speed of execution by this method (a series of singular expansions), we perform the dilation (1) over the entire image, i.e. we choose $X \equiv e^2$. However, this does not particularly contribute to the efficiency of the process, since the length of the series of expansions is expected to be commensurable with the dimensions of the image, i.e. it would be fairly inefficient in processing speed.

Therefore, we propose an alternative calculation of the maximal series, a simultaneous one for all possible series of the given image, via the DT-map of the image. We'll be using the most efficient implementation of the distance transformation – namely, the DT-5-7-11, which according to Gunilla Borgefors [2] results in a maximal difference from the respective Euclidian distance less than 2%. At the same time, the execution speed of DT-5-7-11 is comparable to that of a single dilation (1).

An illustration of a DT-5-7-11 performance is given in Fig.2a. We will consider this DT later in the paper to describe our method for random series of singular expansions of shapes in the image, as we refer to the CET. It should be only marked here that we apply the above described congruence: DT $\Leftrightarrow$ {series of dilations (1)}, for mostly intuitive reasons. A stricter theoretical analysis would show that the proposed method via DT is rather isomorphic to a series of open/close operations [8] over the given image. However, the latter does not significantly change the main idea of using DT.

3. CONTOUR EVOLUTION TREE (CET)

CET is a convenient programming structure, whose relevance to the examined problem was already briefed in Section 2. Now we have to illustrate an algorithm for its implementation.

For efficiency, CET stores only the contours of the black shapes utilizing classical algorithms for contouring [1, 4, 6, 7, 8].

3.1. Building the tree

We construct the CET in the process of the above-described consecutive expansion of the shapes in the image. We create a *node* for every available shape at every stage of expansion, i.e. CET level. The respective nodes between two successive levels are joined with a *rib*. When two or more shapes of the preceding level are grouped (merged), the newly created node is referred to as a *parent* of the particular merged shapes (*successors*). In other words, the tree looks inverted (see Fig.3). That is, if by programming traditions the root is located at the top (the root corresponds to the image frame), then the original image is represented by the leaves (on the bottom), and the expansion process evolutes 'bottom-up' (Fig.3).

Thus constructed, the tree clearly shows that the shapes branched minimally and located closely to the root have a tendency of being *artifacts.* Similarly, the shapes, which are located deeply in the tree, and which are begotten by a significantly branching parent have to be considered relevant *objects*, i.e. parts of a trademark in our case.

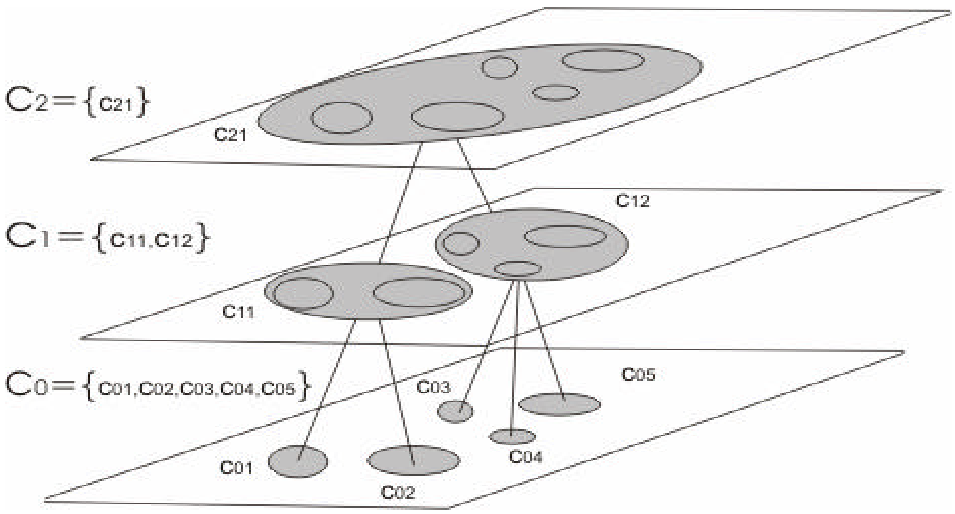


Fig.3. Illustration of the CET for a given image (at the bottom). The expansion and shape grouping process develops bottom up.

3.2. Optimization of CET construction via DT.

Clearly, the DT-map of the given image harbors the same information, which underscores the very evolution tree. We could imagine the result of the DT as relief map, which iso-lines are defined over the pixels of equal distance (to the image object(s)). Thus, the move from the CET leaves to the CET root can be interpreted as moving down the slope (of the relief), in this way creating bigger and bigger degrees of grouping (merging) – see also the illustration in Fig.2.

Thus, the idea of optimizing the computation of a random series of expansions via the DT-map appears (almost) obvious. The fact that the number of merging shapes is monotonically decreasing with every ensuing step of expansion (evolution), is employed considerably – see also the illustration in Fig.1.

Therefore, registering of shape grouping can be achieved by applying a fast method for binary search for (all necessary) CET levels of evolution collisions. Moreover, if the number of shapes at two different levels of the CET is the same, then this number is the same in the respective interim levels, i.e. these levels can be skipped during the search.

4. TWO APPROACHES FOR ANALYZING THE CET

Having the constructed CET we need to analyze its structure to distinguish the relevant objects from the artifacts. The following two approaches have been experimented.

4.1. A cut CET approach (with a stopping rule)

This approach idea consists in finding the evolution stage whereat to stop the evolution (expansion) of the image. The picture we expect to see at that stage is the one in which the expanded central shape covers the major part of the trademark components, while the other united surrounding shapes can be considered noise-artifacts. However, the experiments discredit this primary idea. It works only in simple cases of comparatively small number of shapes, and in very special disposition of them. Therefore, this approach has been described only for reasons of initial analysis of our use case.

4.2. A full CET approach (with weight coefficients over the nodes)

The CET gives a good visual picture, but not an accurate indication whether and to what degree given shapes are *artifacts*. We can gain to such a conclusion by introducing weight coefficients in the CET nodes by the following simple algorithm. First, we assign a value of 1 to the root. Next, every interim node gets an equal share of the weight of the parent with that of its successors. For example, if a given node is assigned a weight of k and branches off to n number of successors, then every successor can get a weight k_i:

$$k_i = k \,/\, n \;,\; i = 1,2,\ldots n \;. \qquad (2)$$

Noticeably, (2) well corresponds to the criteria defined in the Section 2.1, namely:

- to criteria 1: weights are reciprocal to respective number of objects in given area;

- and to criteria 2: weights are reciprocal to respective distances from the group of objects in this area. Besides, the sum of the weights of the leaves equals 1, which prompts us to interpret them as probabilities.

4.3. Final reconstruction of the "cleaned-up" image

First, a new image shell is created full of a background, which color/intensity is the closest to the original one and upon which the output image will be overlaid. Every (x, y) pixel from a shape, recognized as an *object*, is superimposed over the respective (x, y) pixel of the new image, but with a "transparency degree" equal to its currently shaped value. This technique is known in computer graphics under the name - *Alpha Blending* [1] and can be expressed by the following assignment operator:

$$r := o * (1- k) + r * k \;, \qquad (3)$$

where o is the value of the original pixel, r is its value at the given shape from the CET, and k is the weight coefficient of the respective shape, calculated by (2).

The consequentially observed effect is that the output image contains the entire original one, but the intensity of the *artifacts* is closer to that of the background, which reflects their suppression/reduction. If a complete exclusion of artifacts is required, *binarization* can be applied as an ensuing step, for example, binarization with a global optimal threshold by Otsu [5].

A simple technique to find the closest intensity to the one of the background is to locate the most prevalent intensity in the periphery of the image, where the probability of expecting dominating background to object intensities is the highest.

5. EXPERIMENTAL RESULTS

To evaluate the contribution of the proposed (*geometrically-morphological*) filter to the noise-resistance of the target system EFIRS in its practical application at PORB, we conducted tests over a set of actual images, cordially provided by PORB.

The testing approach we chose allows estimating the improvement of EFIRS recognition rate when applying the proposed filter. To achieve an independency from the current stage of EFIRS development we apply an indirect experimental schema. Thus, we conducted two types of tests**:** (1) Filter + EFIRS and (2) EFIRS without preliminary filtering.

The specific test image database (IDB) contains 584 (= 4 x 146) images, which are structured in 4 test sets as follows:

- The first two sets are: the set {**o**} of the original 146 images and the set {**c**} of the same images, but preliminary manually cleaned up from noise-artifacts.

- The other two sets are {**o1**} and {**c1**}, which correspond to {**o**} and {**c**}, upon which the proposed filter has been already applied.

We have organized a separate IDB, accordingly entitled, for each of the 4 sets of images (see Fig.4). Thus we can realize two test: (T1) applying EFIRS on **IDB_o1** and/or **IDB_c1,** and (T2) applying EFIRS on **IDB_o** and/or **IDB_c.**

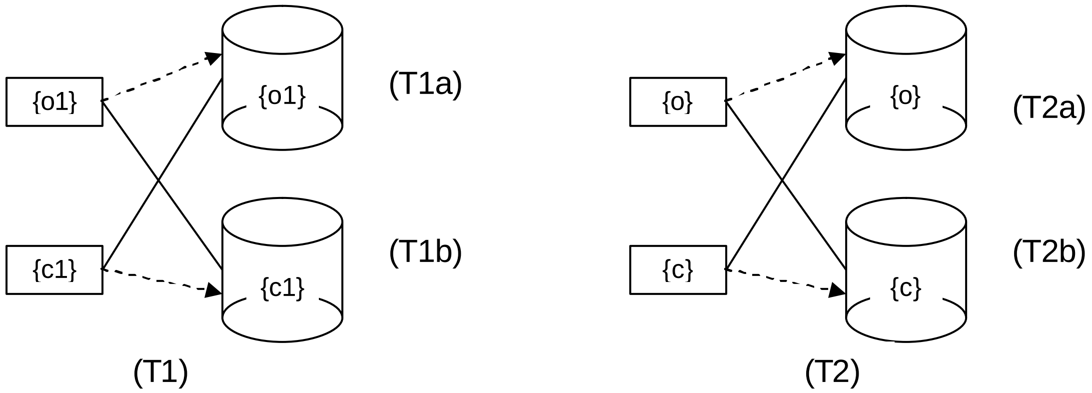


Fig.4. A schematic presentation of both test experiments:
T1) Search after preliminary filtering: a) **IDB_c1** containing the set of images {**c1**} is being searched for matching images from {**o1**}, and reversely b) for **IDB_o1** and {**c1**};
T2) Direct search, without any filter: a) **IDB_c** containing the set of images {**c**} is being searched for matching images from {**o**}, and reversely b) for **IDB_o** and {**c**}. By the way, a same-name search (by the dotted lines) is out of interest, as it theoretically (and in practice) results in 0 retrieval errors.

For instance, for the first case (Filter + EFIRS) we search: (T1a) with the set {**o1**} in **IDB_c1**, and (T1b) with the set {**c1**} in **IDB_o1** (see Fig.4). This completely simulates the targeted situation - a CBIR access method expanded by the proposed filter. The results of these two tests should be quite close, that is, if there are any retrieval errors, they will mostly be the same in both tests. Any potential errors can be ascribed to imperfections of the tested system itself (EFIRS, in our case), but not to its expansion (with the proposed filter).

The other two test combinations, the tested system alone, without any preliminary filtration, i.e. T2a) by the set {**o**} in **IDB_c**, and T2b) by {**c**} in **IDB_o**, are naturally expected to result in a much higher error of image retrieval.

A same-name search, that is {**o1**} in **IDB_o1**, and {**c1**} in **IDB_c1**, as well as {**o**} in **IDB_o**, and {**c**} in **IDB_c**, makes sense for the evaluation of only the basic access method, but not of its improvement by an auxiliary filter. The same-name-search would only demonstrate the accuracy of the chosen CBIR access method the target system EFIRS gives up, i.e. whether it can correctly retrieve images of given IDB, searching them in the same IDB. Therefore, the two primary IDB's (**IDB_c** and **IDB_o**) must be different; the system does not "know" which of them is "clean" and which is "dirty". The premise is that EFIRS assures some minimal noise-resistance, which will cover any small differences, resulting from filtering of 'roughly' noised images, that is, if the respective images in {**o**} and {**c**} turn out to be very different.

The evaluation of the improvement resulting from applying the filter is being determined by the ratio between the respective retrieval errors encountered by both type of tests, (T1) and (T2):

$$err\_no\_filter = \frac{Err(o \to c) + Err(c \to o)}{|o| + |c|} \quad , \tag{4}$$

$$err\_with\_filter = \frac{Err(o_1 \to c_1) + Err(c_1 \to o_1)}{|o_1| + |c_1|} \quad , \tag{5}$$

$$improvement = \frac{err\_no\_filter}{err\_with\_filter} = \frac{Err(o \to c) + Err(c \to o)}{Err(o_1 \to c_1) + Err(c_1 \to o_1)} \quad . \tag{6}$$

Table 1 contains the results of a few CBIR experiments we undertook. These CBIR access methods, given up by EFIRS, are referred to as "keys." We considered two types of errors. "Subtle" errors mark the cases of multiple retrieval, i.e. a number (more than 1) of retrieved images that are not distinguish by the system. "Rough" errors are the ones related to a retrieval of nothing.

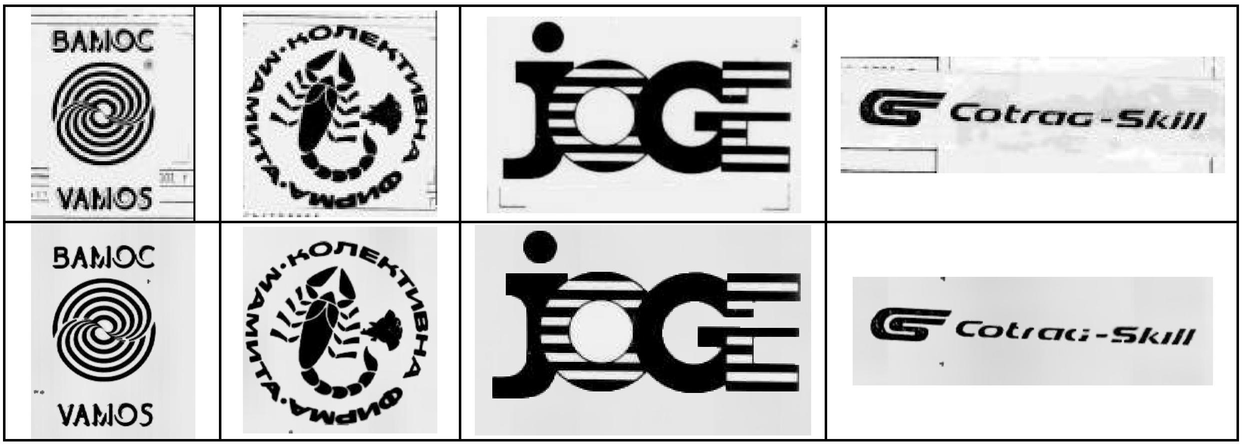
Table 1. Test results of applying the proposed *geometrically-morphological* filter.

IDB	Error Types	Key *E1*	Key *E2*	Key *E3*
	without any filter			
c -> **o**	Subtle	16	32	10
	Rough	60	56	92
	Total	76	88	102
o -> **c**	Subtle	20	31	10
	Rough	60	53	88
	Total	80	84	98
Total for **{o}** and **{c}**	Total Subtle/Rough	156 36/120	172 63/109	200 20/180
Improvement value		**2.14**	**1.91**	**1.65**
	with the proposed filter			
Total for **{o1}** and **{c1}**	Total	73	90	121
c_1 -> **o_1**	Subtle	16	28	10
	Rough	19	20	52
	Total	35	48	62
o_1 -> **c_1**	Subtle	17	21	10
	Rough	21	21	49
	Total	38	42	59

Analyzing comparatively the number and type of errors resulting from both tests, (T1) and (T2), we find out an improvement of about 2 times, i.e. the percentage of error reduction when applying the proposed fitter is about 50%. We consider this a good proof of the effectiveness of the proposed *geometrically-morphological* method for eliminating artifact-noise in trademark images.

Examples of the filter application on 4 trademark images of from the practice of PORB are given in Table 2.

Table 2. Input images (top row) and the here filtered ones (bottom row).



CONCLUSION

The proposed method for artifact suppression (elimination) is based on an approach, exploring the contours of shapes in an image from the standpoint of the distances between them. The method underscores groups of contours that are related by their geometric proximity. The same idea is applied recursively over the so-formed groups as new shapes. Thus, the newly defined structure – Contour Evolution Tree – illustrates the closeness of the contour groups at all levels. The tree allows for interpretations of a variety of heuristic approaches for analysis and evaluation of tasks related to segmenting of rough artifact-noise in images.

Two approaches were investigated in this report: (1) by splitting the CET using a stopping rule, and (2) by a probability evaluation of the entire CET, in this way evaluating the every shape in the original image, whether and to what degree it could be interpreted as a noise artifact. The above evaluation is then used at the final stage of reconstructing the image, in eliminating the thus-segmented noise. The proposed method is valid for random images, not only black-and-white ones. We examined the later in order only to present the proposed method essence**.**

Future work will involve perfecting the proposed geometrically-morphological filter by improving the approach for evaluating the nodes of the tree.

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