# Accelerating Image Retrieval using Binary Haar Wavelet Transform on the Color and Edge Directivity Descriptor

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***Abstract*—In this paper, a new accelerating technique for content-based image retrieval is proposed, suitable for the Color and Edge Directivity Descriptor (CEDD). To date, the experimental results presented in the literature have shown that the CEDD demonstrates high rates of successful retrieval in benchmark image databases. Although its storage requirements are minimal, only 54 bytes per image, the time required for the retrieval procedure may be practically too long when searching on large databases. The proposed technique utilizes the Binary Haar Wavelet Transform in order to extract from the CEDD a smaller and more efficient descriptor, with a size of less than 2 bytes per image, speeding up retrieval from large image databases. This descriptor describes the CEDD, but not necessarily the image from which is extracted. The effectiveness of the proposed method is demonstrated through experiments performed with a known benchmark database.**

***Keywords*-CEDD; Image Retrieval; Large Scale Databases**

## I. Introduction

As the use of computers, internet and cameras is getting more popular by the minute, efficient content-based image retrieval is more essential than ever. Any technology that, in principle, helps to organize digital image archives by their visual content is defined as Content based image retrieval (CBIR). By this definition, anything ranging from an image similarity function to a robust image annotation engine falls under the purview of CBIR [1].

Online image repositories such as Flickr contain hundreds of millions of images and are growing quickly [2]. The requirements of the modern retrieval systems are not limited to the achievement of good retrieval results, but extend to their ability for quick results. The majority of the internet users would compromise the partial reduction of the results accuracy in order to save time from searching.

The image retrieval, as well as text retrieval, may be described by the similarity search paradigm [3]. Efficient approaches that allow application on generic similarity search problems still need to be investigated [4]. A promising direction to address this issue is the *approximate* similarity search paradigm [5], [6], [7], [8]. Approximate similarity search provides an improvement in similarity search performance at the price of some imprecision in the results. An interesting approach of approximate similarity search was proposed in [4]. The idea at the basis of this technique is that when two objects are very close one to each other they 'see' the world around them in the same way.

In order to achieve image retrieval from large scale databases, the representation of images by Latent Dirichlet Allocation (LDA) [9] models for content-based image retrieval is studied in [2]. Image representations are learned in an unsupervised fashion, and each image is modeled as a mixture of its depicted topics or object parts.

The present paper proposes a different approach for searching in large databases. First of all, in order to ensure quality of the results, the Color and Edge Directivity Descriptor (CEDD), proposed in [10], [11], is utilized. The size of this descriptor is 54 bytes/image. Subsequently, the Binary Haar Wavelet Transform [12] applied on the CEDD, is used for the extraction of a second descriptor. This second descriptor, which describes the CEDD content with less than 2 bytes, is employed during the retrieval procedure instead of the image. In this way, reduced retrieval times are achieved. Details concerning the CEDD and the Binary Haar Wavelet Transform are given in Sections 2 and 3, respectively.

During the search process, an image query is entered and the system returns images with a similar content. Initially, the similarity/distance between the query and each image in the database is calculated with the proposed descriptor, and only if the distance is smaller than a predefined threshold, the comparison of their CEDDs is performed. The entire retrieval procedure is described in Section 4. In order to estimate the appropriate threshold value, efficient techniques, described in Section 5, were used. The experimental results are presented in Section 6, and the conclusions of this study are drawn in Section 7.

## II. The Color and Edge Directivity Descriptor

The descriptors which include more than one features in a compact histogram can be regarded that they belong to the family of Compact Composite Descriptors. A typical example of CCD is the CEDD descriptor. The structure of CEDD consists of 6 texture areas. In particular, each texture area is separated into 24 sub regions, with each sub region describing a color. CEDD's color information results from 2 fuzzy systems that map the colors of the image in a 24-color custom palette. To extract texture information, CEDD uses a fuzzy version of the five digital filters proposed by the MPEG-7 EHD [13], [14]. The CEDD extraction procedure is outlined as follows: When an image block (rectangular part of the image) interacts with the system that extracts a CCD, this section of the image simultaneously goes across 2 units. The first unit, the color unit, classifies the image block into one of the 24 shades used by the system. Let the classification be in the color $m, m \in [0, 23]$. The second unit, the texture unit, classifies this section of the image in the texture area $a, a \in [0, 5]$. The image block is classified in the bin $a \times 24 + m$. The process is repeated for all the image blocks of the image. On the completion of the process, the histogram is normalized within the interval [0,1] and quantized for binary representation in a three bits per bin quantization.

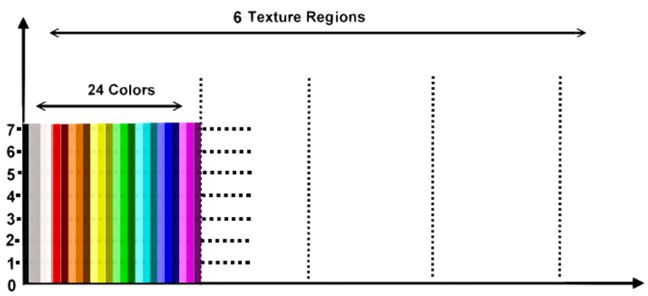


Figure 1. The structure of the CEDD.

The most important attribute of CEDDs is the achievement of very good results that they bring up in various known benchmarking image databases. Table 1 shows the ANMRR [13] results in 3 image databases, along with those obtained by MPEG-7 descriptors. The ANMRR ranges from '0' to '1', and the smaller the value of this measure is, the better the matching quality of the query. ANMRR is the evaluation criterion used in all of the MPEG-7 color core experiments. Evidence shows that the ANMRR measure approximately coincides linearly with the results of subjective evaluation of search engine retrieval accuracy. More details on the ANMRR are given in section 6. The ANMRR values for the MPEG-7 descriptors in WANG's [15] database as well as the ground truths that were used are available at [16]. Since MPEG-7 descriptor results are not available for the UCID [17] and NISTER [18] databases, an implementation of CLD, SCD and EHD in img(Rummager) [19] and LIRe Demo [20] retrieval systems is used. Details regarding the experimental results, the implementation of the MPEG-7 descriptors, as well as the ground truths that were used, are available online.

Another important attribute of CEDD is its small size requirements for indexing images. The CEDD length is 54 bytes per image.

| Descriptor | WANG | UCID | NISTER |
|---|---|---|---|
| CCD | | | |
| CEDD | **0.25283** | **0.28234** | **0.11297** |
| MPEG-7 | | | |
| DCD MPHSM | 0.39460 | - | - |
| DCD QHDM | 0.54680 | - | - |
| SCD | 0.35520 | 0.46665 | 0.36365 |
| CLD | 0.40000 | 0.43216 | 0.2292 |
| CSD | 0.32460 | - | - |
| EHD | 0.50890 | 0.46061 | 0.3332 |
| HTD | 0.70540 | - | - |

Table I
ANMRR RESULTS IN THREE BENCHMARK IMAGE DATABASES.

The img(Rummager) and LIRe Demo retrieval systems use these descriptors to create index files from which they carry out the search. Img(Rummager) makes XML-type index files, while LIRe utilizes a Lucene index to store the descriptors.

## III. MODIFIED BINARY HAAR WAVELET TRANSFORM

The Binary Haar Wavelet Transform coefficients of the histogram are calculated with the use of following Haar Wavelet Transform [12]:

$$\psi(x) = \begin{cases} 1 & 0 \leq x < 0.5 \\ -1 & 0.5 \leq x < 1 \\ 0 & else \end{cases} \quad (1)$$

Figure 2 shows the four basis functions of the Haar wavelet of length eight. The Haar wavelet coefficients are obtained by taking the inner product of the basis functions with the given histogram. This transformation is very fast as it does not involve multiplications.

The Haar coefficients capture the qualitative aspects of the histogram [21]. For example, the second coefficient (from the basis function 2 in Figure 2) is positive if the sum of the left half of the histogram bins is greater than the right half and negative otherwise. Similarly, the third coefficient is positive if the sum of the first quarter of the histogram bins is greater than the second quarter and negative otherwise. In the Binary Haar descriptor, each of these coefficients is quantized to '0' or '1', depending on whether its value is negative or positive, hence a binary representation is obtained.

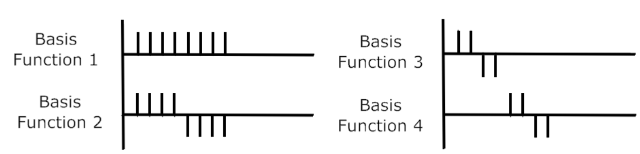


Figure 2. Four basis functions of the Haar wavelet of length eight.

At the first level, the $k$ bins of the histogram are divided into two halves. If the sum of the histogram values in the left half is greater than the sum of the histogram values in the right half then the second bit of descriptor is '1', while is '0' otherwise. Note that the first coefficient corresponds to the sum of all probabilities in a histogram and it is always positive. Therefore is quantized to 1 and is not used in similarity matching.

At the second level, the $k/2$ bins of each half of the histogram are divided into two halves. If the sum of the histogram values in the first half is greater than the sum of the histogram values in the second half then the second bit of descriptor is '1' else it is '0'. Similar, if the sum of the third half is greater than the sum in the fourth half, then the third bit of descriptor is '1' else it is '0'. This is repeated recursively for the third and the fourth level.

For the application of the Binary Haar Wavelet Transform to the CEDD descriptor we work as follows: First, we isolate the color and texture information from the descriptor in two independent vectors, the CEDD_Color vector consisting of 24 elements and the CEDD_Texture vector consisting of 6 elements. The separation is straightforward since each information item is distinctively placed in the descriptor. The separation pseudocode is given in the following:

```
for (int i = 0; i < 6; i++)
  {
   for (int j = 0; j < 24; j++)
      {
          CEDD_Color [j] += CEDD[24 * i + j];
      }
   }
for (int i = 0; i < 6; i++)
  {
   for (int j = 0; j < 24; j++)
    {
     CEDD_Texture [i] += CEDD[24 * i + j];
    }
   }
```

The Binary Haar Transform is applied on the CEDD_Color vector up to the third level resulting in 7 coefficients (1 coefficient from the first transformation level, 2 coefficients from the second transformation level, and 3 from the third level).

Regarding the CEDD_Texture vector, given that the resulting 2 halves include 3 elements, the problem arising is that the transform may be applied only once. In order to overcome this constraint, whenever this is met during the transform application, we propose the following solution:

During the first transform level, the 6 elements are divided in 2 triads. To apply the second level, the middle element of each triad is cloned. The 2 identical elements replace the original element from which they came from. In this way, each triad is replaced by a quartet of elements, on which now the transform may be applied. In the third level of the Binary Haar Transform the cloned elements are removed and the transform is applied directly on the vector, comparing, this time, the elements per pair. On the whole, 8 elements are created (1 from the first transform level, 4 from the second level and 3 from the third). The complete extraction procedure of the Modified Binary Haar Wavelet Transform from CEDD_Texture is illustrated in Figure 3.

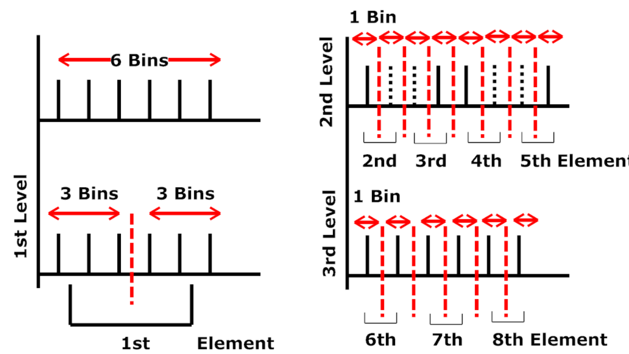


Figure 3. Extraction procedure of the Modified Binary Haar Wavelet Transform from CEDD_Texture.

At the end of the procedure, the 2 resultant vectors are placed consecutively. From this point and for the rest of this paper, the result obtained from the application of the Binary Haar Transform on the CEDD descriptor will be referred as Binary CEDD (B-CEDD). Its size is limited to 15 binary bins and its storage requirements are much smaller than 2 bytes per image (15 bits).

## IV. System Overview

One of the most important attributes of the Binary CEDD (B-CEDD) is that is extracted directly from the CEDD, with no intervention of the described image. This results in its immediate extraction from the already existent index files.

The searching procedure based on the use of the 2 descriptors, CEDD and B-CEDD, is illustrated in Figure 4. The user enters a query image in the system. From this image, both the CEDD and the B-CEDD descriptors are extracted. The system uses an image database in which the indices are described by both descriptors. During data retrieval from databases, the length of the retrieved information is of great significance [22]. For this reason, in a first phase the system retrieves only the B-CEDD descriptor, which, due to its small storage requirements, as well as its small length, is retrieved instantly.

For each indexed in the database image, the distance between the B-CEDD descriptor with the corresponding B-CEDD descriptor of the query image, is calculated by a simple X-OR gate. In the case of 2 identical descriptors, the X-OR output is equal to 0, while in the worst scenario the obtained distance is 15 (equal to the B-CEDD length). The logic gate X-OR requires much less computational cost than the Tanimoto coefficient. Tanimoto coefficient is used to calculate the distance between CEDD descriptors.

If the distance of the 2 descriptors is found to be smaller than $T$, then the CEDD descriptor is retrieved from the database and its distance from the corresponding CEDD descriptor of the query image is calculated. The procedure is repeated for all the database images.

After the completion of the procedure, the classified results are shown to the user in ascending order of the distance obtained during the CEDD descriptors comparison.

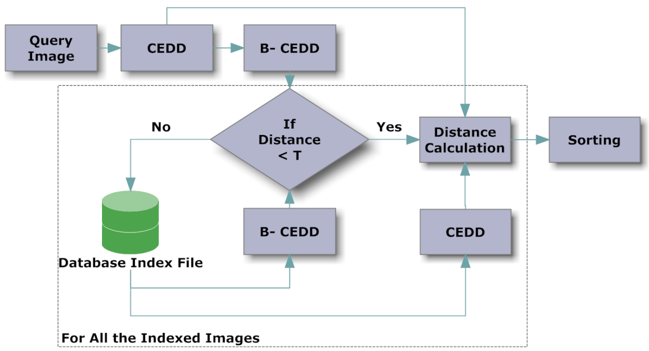


Figure 4. Searching using the 2 descriptors.

The most important issue that should be taken into consideration during the aforementioned procedure is the determination of the threshold $T$. This threshold defines whether an image is potentially similar to the query image. In this case the retrieval of the image's CEDD is requested and the process for its comparison with the corresponding CEDD of the query image is activated. The $T$ value investigation is described in detail in the following section.

## V. Investigating the $T$ Value

In order to determine the most appropriate $T$ value we work as follows: We choose 20 images from the Wang database and regard them as historical queries. The historical queries idea comes from the text retrieval area and has been used to normalize results in cases of fusion and distributed information retrieval [23], [24].

For each one of the historical queries, searching is performed in the database from which they originate. In particular, the distances between the B-CEDD descriptors of each historical query and each image of the database are calculated and a ranking list, in which the database images are ordered according to their distance from the historical query, is obtained. The procedure is repeated for all the historical queries. At the end of the process, 20 ranking lists emerge. Since that the Wang database includes 1000 images, 20000 values (20 ranking list $\times$ 1000 images) are finally obtained. By plotting these values the distances distribution is obtained (Figure 5). Subsequently, the set of these values enters in a Gustafson Kessel fuzzy classifier [25].

The Gustafson Kessel is an extension of the Fuzzy C-Means algorithm that deals with this problem by using the covariance matrix in order to detect ellipsoidal classes. The Gustafson Kessel parameters are selected as: Clusters=4, Repetitions=3000, $e = 0.001$ and $m = 2$. The classifier output is shown in Figure 6. The four resulting classes are used in order to form a single input fuzzy system. The vertical axis shows the distance that may be obtained during the comparison of the 2 B-CEDD descriptors, while the horizontal axis shows the activation degree for the membership function of each class.

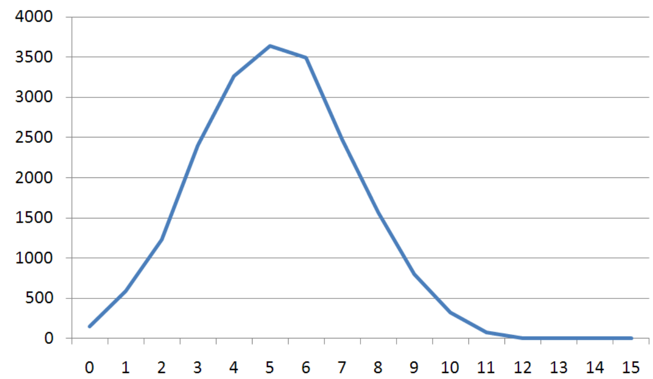


Figure 5. Distribution of the B-CEDD distances for 20 historical queries.

Consider, for instance, that the distance between 2 images was found to be equal to 4 (see Figure 6). This value activates both the first and the second class for 0.5. Thus, this sample may not be distinctively classified in one of these classes. The classes are labeled as: "Low", "Medium", "High" and "Highest". The system gets as input the distance between the B-CEDD descriptors of the query image and any other image.

For the simplest scenario of the model usage we should specify that if the membership degree of the "Low" function is greater than the membership degree of any other class, then the image under study possibly exhibits visual similarity with the query image. Thus, the CEDD descriptor should be also retrieved in order to perform the comparison.

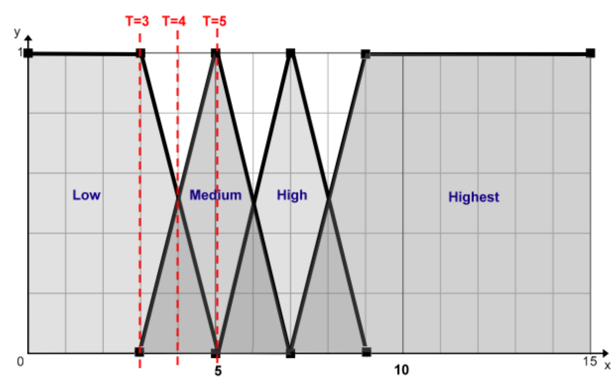


Figure 6. Outcome of the historical queries distances distribution classification in 4 classes.

Similarly, if the "Low" activation degree is smaller than that of another membership function, the image is discarded.

In the next section, the experimental results of a large scale threshold tuning attempt, that aimed at the results improvement, are presented.

## VI. Experimental Results

Given that the proposed descriptor is an MPEG-7 like descriptor, the schema of the B-CEDD as an MPEG-7 extension is described as follows:

```
<?xml version ="1.0" encoding="UTF-8"?>
<schema xmlns="http://www.w3.org/2001/XMLSchema"
        xmlns:mpeg7="urn:mpeg:mpeg7:schema :2004"
        xmlns:SpCDNS="B-CEDDNS" targetNamespace="B-CEDDNS">
  <import namespace="urn:mpeg:mpeg7:schema:2004"
                                    schemaLocation="Mpeg7-2004.xsd"/>
  <complexType name="B-CEDDType" final="#all">
    <complexContent>
      <extension base="mpeg7:VisualDType">
       <sequence>
         <element name="value">
          <simpleType>
           <restriction>
            <simpleType>
              <listitemType="mpeg7:Binary"/>
            </simpleType>
             <length value="15"/>
           </restriction>
          </simpleType>
         </element>
       </sequence>
      </extension>
    </complexContent>
  </complexType>
</schema>
```

To the best of our knowledge, there is no large scale image database with ground truths data available that could be used for the performance evaluation of the proposed method. For this reason, experiments have been performed in the Wang database. In [16], 20 queries have been proposed in order to evaluate the retrieval systems that utilize the specific database.

For each of these queries the time of the retrieval through the proposed system is measured, as well as the time required when only the CEDD descriptor is used. Moreover, the performance of the system is assessed through the results evaluation. For the performance evaluation the following measures were used:

1) Recall at $n$, where $n$ is the number of the retrieved through the proposed method images. This measure presents the number of relevant documents retrieved by a search divided by the total number of existing relevant documents.
2) ANMRR at $n$. The ANMRR ranges from 0 to 1. The smaller the value of this measure is, the better the matching quality of the query. This measure has the ability to combine both precision and recall in only one value. Given that in a lot of cases the ground truth of each query is only partially retrieved, this measure considers as ground truth solely the retrieved subset of the query ground truth.

The ANMRR computation requires the average rank computation. The average rank AVR(q) for query q is:

$$AVR(q) = \sum_{k=1)}^{NG(q} \frac{Rank(k)}{NG(q)} \tag{2}$$

Where

- $NG(q)$ is the number of ground truth images for the query $q$. In our case $NG(q) = 1$
- $K$ is the top ranked retrievals examined where:
  - $K = min(X \times NG(q), 2GMT)$, $GMT = max(NG(q))$, in our case $K = 2$
  - $NG(q) > 50$ then $X = 2$ else $X = 4$
- $Rank(k)$ is the retrieval rank of the ground truth image. Considering a query assume that as a result of the retrieval, the $k^{th}$ ground truth image for this query $q$ is found at a position $R$. If this image is in the first $K$ retrievals then $Rank(k) = R$ else $Rank(k) = K + 1$

The modified retrieval rank is:

$$MRR(q) = AVR(q) - 0.5 - 0.5 \times N(q) \tag{3}$$

The normalized modified retrieval rank is computed as follows:

$$NMRR(q) = \frac{MRR(q)}{K + 0.5 - 0.5 \times N(q)} \tag{4}$$

The average of NMRR over all queries defined as:

$$ANMRR(q) = \frac{1}{Q} \sum_{q=1}^{Q} NMRR(q) \tag{5}$$

The proposed method is implemented in the retrieval system img(Rummager) [19]. For the exact time measurement, each experiment was repeated 10 times.

As already mentioned in the previous section, the necessity for accurate estimation of the $T$ threshold value which defines whether the CEDD descriptor of an image should be retrieved, is imperative. The fuzzy classifier results in section 5 demonstrated the fact that when $T \leq 3$, the function that classifies the distance to the "Low" class, is activated in a bigger degree of membership. Thus, for the images with B-CEDD distance less than $T = 3$, the CEDD retrieval will be done, and the CEDD will participate normally in the searching procedure. In the examples that follow, an investigation is conducted in order to determine the appropriate value of $T$ that would activate the membership functions for the classification of the images at the "Low" and "Medium" classes, while would simultaneously prevent the activation of any other membership function. That is, an investigation for $T \in [3, 5]$ takes place. These values are depicted in Figure 6 with a dashed line. All the experiments have been performed with an Intel Core 2 Quad Q9550 @2.83GHz PC with 3GB of RAM.

Table 2 illustrates the mean value results for the 20 queries of the Wang database for $T \in [3, 5]$. The Recall index represents the ratio of the correct image retrievals for each query (images that belong to the ground truth of the query) to the size of the ground truth. Therefore, the Recall @ $n$ describes the percentage of the correct images that were retrieved for all the queries. On the other hand, the ANMRR index evaluates the order in which the results were placed after the completion of the procedure. Thus, in order to assess the systems effectiveness properly both 2 measures should be taken into account. Considering these results, it may be readily observed that indeed the proposed method improves the searching procedure times significantly. For $T = 3$, the proposed method is able of retrieving almost 112000 images per second. Although the ANMRR index attains very good levels the Recall @ $n$ index has a very small value. This means that even if, on the average, 218.4 images were retrieved for each query, a lot of images from the ground truth were absorbed. On the other hand, when $T = 5$ god results where achieved for both the Recall @ $n$ and the ANMRR but the searching time was over doubled contrasted to the corresponding time for $T = 3$. The threshold $T = 4$, which retrieves 83333 images per second and its performance is found satisfactory for both the Recall @ $n$ and the ANMRR, could be considered as the 'golden-mean' solution. Compared to the CEDD method, the proposed method with $T = 4$ retrieves almost four times more images per second.

| | $T = 3$ | $T = 4$ | $T = 5$ |
|---|---|---|---|
| CEDD Time | 45ms | | |
| B-CEDD Time | 9 ms | 12ms | 19ms |
| Retrieved Images | 218.4/1000 | 381.45/1000 | 563.15/1000 |
| Recall @ $n$ | 0.5441 | 0.7074 | 0.8675 |
| ANMRR @ $n$ | 0.1611 | 0.1795 | 0.2141 |

Table II
COMPARATIVE RESULTS FOR $T \in [2, 6]$ IN THE WANG DATABASE.

## VII. CONCLUSIONS

In this paper, an extension of the Color and Edge Directivity Descriptor is proposed, which improves the efficiency of the CEDD in large databases. Through the application of the Modified Binary Haar Wavelet Transform on the CEDD, the proposed method achieves the extraction of a second, smaller (15 bits length), descriptor. Essentially, each CEDD descriptor is described by another compact binary descriptor. During the image searching process solely the compact versions of the descriptors are employed, and only when their distance is smaller than a given threshold the searching continues with the CEDD. The distance between the B-CEDD descriptors is calculated by using a simple X-OR gate. The logic gate X-OR has much less computational cost than the Tanimoto coefficient.

One of the most important attributes of the Binary CEDD (B-CEDD) is that is extracted directly from the CEDD, with no intervention of the described image. This enables its immediate extraction from pre-existing index files. The effectiveness of the proposed method was demonstrated through experimental results. Finally, it's worth noting that the proposed method may be applied to all the Compact Composite Descriptors [22], [26], [27].

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