Content-based Watermarking for Indexing Using Robust Segmentation *

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ABSTRACT

In this paper, a novel approach to image indexing is presented using content-based watermarking. Some concepts associated with the application of watermarking to image indexing are discussed and a segmentation algorithm, appropriate for content-based watermarking, is presented. The segmentation algorithm is applied on reduced images and derives the exact same objects when performed on either the original or the watermarked image. In this way, the proposed system does not suffer from synchronization problems that usually occur during watermark detection.

1 Introduction

Watermarking has received significant attention lately due to its applications on the protection of intellectual property rights (IPR) [1, 2]. However, many other applications can be conceived which involve information hiding [3]. In this paper, we propose the employment of watermarking as a means to perform content-based indexing and retrieval of images from data bases.

In order to endow the proposed scheme with content-based functionalities, information must be hidden region-wise in digital images. Thus, the success of any content-based approach depends largely on the segmentation of the image based on its content. In the present paper, an efficient segmentation algorithm is used prior to information embedding.

Embedding indexing information in image objects has the following advantages:

- Each region in the image carries its own description and no additional information must be kept for its description.
- The image can be moved from a database to another without the need to move any associated description.

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The present paper provides an elegant framework for the application of watermarking to image indexing. Despite the fact that, due to the increased computational complexity, the proposed system cannot be used in large data bases at the present time, it clearly demonstrates another potential application of watermarking.

The paper is organized as follows: the system overview is given in section 2. The information embedding method is presented in section 3. In section 4, the segmentation algorithm used with our system is described. In section 5, experimental evaluation is shown, and finally conclusions are drawn in section 6.

2 System overview

The methodology proposed in this paper assumes that the watermarked images will not be subjected to any attacks. The investigation of robust watermarking or copyright protection is beyond the scope of this paper. However, even without attacks, watermark detection is not a straightforward procedure in our content-based framework since the objects of the images, rather than the original rectangular images, are watermarked (see fig. 1). Thus, the first step in the watermark detection process is to segment the image into objects and subsequently, based on this segmentation, to extract the information bits associated with each object (see fig. 2). If during detection, the image is segmented in different regions than those used in the embedding, then

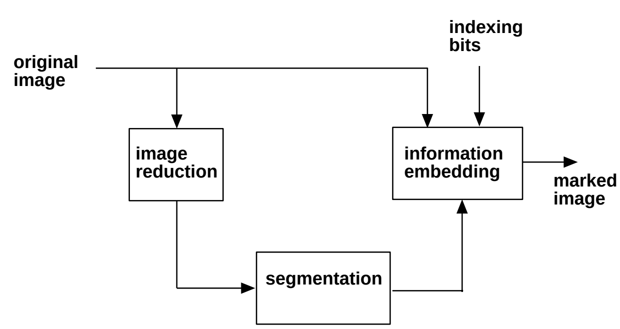

Figure 1: Block diagram of the embedding scheme.

the detection process will not be synchronized with the embedding process and the embedded information will not be retrieved.

In order to combat the loss of synchronization, special care should be taken to make sure that the execution path followed during the embedding process for segmenting the image into objects and the execution path during detection will be identical despite the alteration the image has undergone due to watemarking.

Figure 2: Block diagram of the detection scheme.

For this to be achieved, the algorithm is applied to a reduced image, comprising of the mean values of the pixel intensities in 8×8 pixel blocks of the original image. Thus, if the mean values of the intensities for each such block remain the same after the watermarking process, then the resulting reduced image, to which the segmentation algorithm is applied, is the same regardless of whether it is derived from the original or the watermarked image.

A space-domain information embedding strategy which keeps the mean value of each image block constant is described in the ensuing section.

3 Information embedding

The mean intensity $\bar{I}[l_1, l_2]$ of an 8×8 block in the original image I is

$$\bar{I}[l_1, l_2] = \frac{1}{64}\sum_{i=0}^{7}\sum_{j=0}^{7} I[8l_1 + i, 8l_2 + j]$$

for all three colour components, where l_1, l_2 are the block indexes. We choose to embed the watermark bits in the blue component of the RGB images because the Human Visual System is less sensitive to blue colours [4]. One bit is embedded in each 8×8 block.

The intensities $\bar{I}'[l_1, l_2]$ of the reduced image that will be derived from the watermarked image during detection, are:

$$\bar{I}'_R[l_1, l_2] = \frac{1}{64}\sum_{i=0}^{7}\sum_{j=0}^{7} I_R[8l_1 + i, 8l_2 + j] = \bar{I}_R[l_1, l_2]$$

$$\bar{I}'_G[l_1, l_2] = \frac{1}{64}\sum_{i=0}^{7}\sum_{j=0}^{7} I_G[8l_1 + i, 8l_2 + j] = \bar{I}_G[l_1, l_2]$$

$$\bar{I}'_B[l_1, l_2] =$$

$$\frac{1}{64}\sum_{i=0}^{7}\sum_{j=0}^{7}(I_B[8l_1 + i, 8l_2 + j] + b \cdot a_{l_1,l_2}[i, j] \cdot w[i, j]) \quad (1)$$

where b is the embedded bit (valued -1,1), a is the watermark strength factor, which depends on a local energy measure and is computed seperately for each block in the original image, and $w[i, j]$ is the watermark matrix (see fig. 3) given by

$$w[i, j] = \begin{cases} 1, & \text{if } i + j = \text{even} \\ -1, & \text{if } i + j = \text{odd} \end{cases} \quad (2)$$

1	-1	1	-1	1	-1	1	-1
-1	1	-1	1	-1	1	-1	1
1	-1	1	-1	1	-1	1	-1
-1	1	-1	1	-1	1	-1	1
1	-1	1	-1	1	-1	1	-1
-1	1	-1	1	-1	1	-1	1
1	-1	1	-1	1	-1	1	-1
-1	1	-1	1	-1	1	-1	1

Figure 3: Watermark matrix. The information bit is multiplied by the matrix elements and the strength factor. The resulting signal is added on the image.

The watermark strength a is varied according to the intensity differences of the blue component in the area of the current pixel, as follows:

$$a_{l_1,l_2}[i, j] = \begin{cases} 3, & \text{if } 2T < D_i + D_j \\ 2, & \text{if } T < D_i + D_j \leq 2T \\ 1, & \text{otherwise} \end{cases}$$

where

$$D_i = |I_B[8l_1 + i - 1, 8l_2 + j] - I_B[8l_1 + i + 1, 8l_2 + j]|$$

$$D_j = |I_B[8l_1 + i, 8l_2 + j - 1] - I_B[8l_1 + i, 8l_2 + j + 1]|$$

and the threshold T was experimentally set to 10.

Equation (1) yields

$$\bar{I}'_B[l_1, l_2] = \frac{1}{64}\sum_{i,j} I_B[8l_1 + i, 8l_2 + j] + \frac{1}{64}\sum_{i,j}(b \cdot a_{l_1,l_2}[i, j] \cdot w[i, j]) =$$

$$= \bar{I}_B[l_1, l_2] + \frac{b}{64}\sum_{i+j:even}(a_{l_1,l_2}[i, j] \cdot 1) + \frac{b}{64}\sum_{i+j:odd}(a_{l_1,l_2}[i, j] \cdot (-1)) =$$

$$= \bar{I}_B[l_1,l_2] + \frac{b}{64}\left(\sum_{i+j:even} a_{l_1,l_2}[i,j] - \sum_{i+j:odd} a_{l_1,l_2}[i,j]\right) \tag{3}$$

In order to make sure that the application of the segmentation algorithm to either the original or the watermarked image produces the same results, the mean block intensities of the block (l_1, l_2) should be equal, i.e

$$\bar{I}'_B[l_1,l_2] = \bar{I}_B[l_1,l_2]$$

From (3), it is seen that the above equation is equivalent to

$$\sum_{i+j:even} a_{l_1,l_2}[i,j] = \sum_{i+j:odd} a_{l_1,l_2}[i,j] \tag{4}$$

Thus, the equality of the mean block intensities can be achieved by appropriately modifying the watermark strength factor $a_{l_1,l_2}[i,j]$, after it has been calculated, so that condition (4) is met. In our scheme this is done by reducing the values of $a_{l_1,l_2}[i,j]$, for $i+j$: *even* or $i+j$: *odd*, depending on which sum is greater.

4 Segmentation algrithm

Segmentation methods for 2D images may be divided primarily into region-based and boundary-based methods. Region-based approaches [5] rely on the homogeneity of spatially localised features such as gray level intensity and texture. Region-growing and split and merge techniques also belong to the same category. On the other hand, boundary-based methods use primarily gradient information to locate object boundaries. In this paper, a region-based approach is taken. The image segmentation algorithm consists of three stages:

1. An initial estimation of the number of a connected regions and their colour and spatial centers.

2. An iterative pixel classification process that uses the initial estimations as a starting point.

3. A feature extraction process for indexing purposes.

For notational simplicity, the reduced image to which the segmentation algorithm is applied will be heareafter denoted as I. An initial estimation of the number of classes contained in the (reduced) image is produced by dividing the image into N non-overlapping blocks, each represented by the mean values of the three colour coordinates of the CIE L*a*b* colour space [6], $\bar{\mathbf{I}}_n = (\bar{I}_{L,n}, \bar{I}_{a,n}, \bar{I}_{b,n})$, $n = 1,\ldots,N$, and applying the maximin algorithm to the set of blocks. The colour distance between two blocks is defined as:

$$\|\bar{\mathbf{I}}_m - \bar{\mathbf{I}}_n\| = \sqrt{(\bar{I}_{L,m}-\bar{I}_{L,n})^2 + (\bar{I}_{a,m}-\bar{I}_{a,n})^2 + (\bar{I}_{b,m}-\bar{I}_{b,n})^2}$$

A simple K-means algorithm [7] is then used to classify each block to one of the classes; those classes that do not form connected regions are split, so that K connected regions s_k are formed; the mean values of the colour and space coordinates over the set of blocks of each region constitute an initial estimation of the colour centers $\bar{\mathbf{I}}_k = (\bar{I}_{L,k}, \bar{I}_{a,k}, \bar{I}_{b,k})$, and spatial centers $\bar{\mathbf{S}}_k = (\bar{S}_{x,k}, \bar{S}_{y,k})$, $k = 1,\ldots,K$. These centers are used as a starting point by the pixel classification algorithm: a K-Means-with-connectivity-constraint algorithm. The distance of a pixel $p = (p_x, p_y)$ from a region s_k is defined as follows:

$$D(\mathbf{p},k) = \|\mathbf{I}(\mathbf{p}) - \bar{\mathbf{I}}_k\| + \frac{\lambda}{A_k}\|\mathbf{p} - \bar{\mathbf{S}}_k\|$$

where $\|\mathbf{I}(\mathbf{p}) - \bar{\mathbf{I}}_k\|$ is the colour distance:

$$\|\mathbf{I}(\mathbf{p}) - \bar{\mathbf{I}}_k\| = \sqrt{(I_L-\bar{I}_{L,k})^2 + (I_a-\bar{I}_{a,k})^2 + (I_b-\bar{I}_{b,k})^2}$$

$\|\mathbf{p} - \bar{\mathbf{S}}_k\|$ is the spatial distance:

$$\|\mathbf{p} - \bar{\mathbf{S}}_k\| = \sqrt{(p_x-\bar{S}_{x,k})^2 + (p_y-\bar{S}_{y,k})^2}$$

A_k is the area of the region s_k, defined as $A_k = M_k$, where M_k is the number of pixels assigned to s_k, and λ is a regularisation parameter. The K-Means-with-connectivity-constraint algorithm features region splitting of non-connected regions and merging of chromatically similar neighboring regions. The region centers are recalculated on every iteration as the mean values of the colour and space coordinates over the set of pixels assigned to each region. If M_k elements are assigned to s_k then

$$\bar{\mathbf{I}}_k = \frac{1}{M_k}\sum_{m=1}^{M_k} \mathbf{I}(\mathbf{p}_m^k) \ , \tag{5}$$

$$\bar{S}_k = \frac{1}{M_k}\sum_{m=1}^{M_k} p_m^k, \tag{6}$$

where $\mathbf{p}^k = (p_x^k, p_y^k)$ are the pixels assigned to region s_k. The centers corresponding to regions that fall below a size threshold are omitted. As soon as the K-means-with-connectivity-constraint algorithm converges, regions smaller than a specified threshold are appended to other regions, to ensure that no particularly small, meaningless regions are formed. Finally, a set of features is extracted for every region; those include colour, position, size, and shape features.

5 Experimental results

The watermarking and segmentation algorithms described in the previous sections were tested for embedding information in a variety of colour test images (Fig.

4). 256 bits were embedded on each image object. The embedded information was the values of the features used by the ISTORAMA[1] content-based image retrieval system. Alternatively, any other kind of object-related information could be embedded, including a short text describing the object. The bits were embedded in the blue component of RGB images using the procedure described in section 3. No perceptual degradation of image quality was observed.

Almost all embedded bits could be reliably extracted from the watermarked image. Only a tiny portion ($\leq 0.1\%$) of the total embedded bits were extracted in error. For this reason, simple channel coding was used to ensure errorless information extraction.

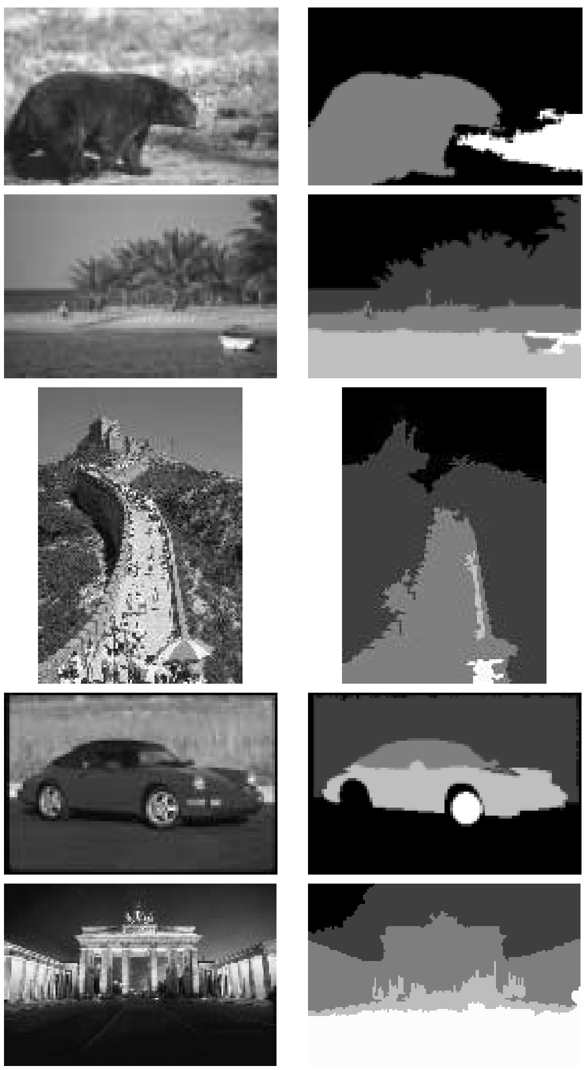

Figure 4: Images segmented into regions.

[1] http://uranus.ee.auth.gr/Istorama

6 Conclusions

A methodology was presented for the content-based embedding of indexing information in digital images. Watermark information is embedded after images are segmented into objects. The watermarking algorithm does not change the mean value of image blocks so that the same objects are extracted during embedding and detection.

The proposed system is appropriate for retrieving images from small data bases only, since the need for segmentation at the detector may be computationally intensive, delaying the process. However, it demonstrates a potentially useful application of watermarking.

7 References

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