A MULTI-SCALE LAYOUT DESCRIPTOR BASED ON DELAUNAY TRIANGULATION FOR IMAGE RETRIEVAL

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Abstract: Working with large collections of videos and images has need of effective and flexible techniques of retrieval and browsing. Beyond the classical color histogram approaches, the layout information has proven to be a very descriptive cue for image description. We have developed a descriptor that encodes the layout of an image using a histogram-based representation. The descriptor uses a multi-layer representation that captures the saliency of the image parts. Furthermore it encodes their relative positions using the properties of a Delaunay triangulation. The descriptor is a compact feature vector which content is normalized. Their properties make it suitable for image retrieval and indexing applications. Finally, have applied it to a video browsing application that detects characteristic scenes of a news program.

1 INTRODUCTION

In recent times, the availability of image and video resources on the World-WideWeb has increased tremendously. This has created a demand for effective and flexible techniques for automatic image retrieval and video browsing. The early content-based image image retrieval (CBIR) systems used techniques such as color histograms because they were easy to compute, robust, and fairly effective (Swain and Ballard, 1991). Nevertheless, the lack of spatial information makes color histograms susceptible to introduce false positives for image retrieval purposes. Then, a wide variety of techniques have been developed to encode the spatial layout of the image content.

Some of these techniques consist in refinements of the color histograms by the spatial coherence of pixels. Two examples are the color coherence vector (CCV) (Pass and Zabih, 1996) and the color correlograms (Huang et al., 1997). CCV compute the color histogram of those coherent pixels of the image, defining coherent as belonging to some sizable region of the image. In a more precis way, color correlograms express how the spatial correlation of color changes with distance. Even thought this kind of techniques are compact, simple and easy to compute, they hardly relay on the image quantization.

Another approach consists in segment the image into regions and include shape information of the regions. A union of heuristic shape features (bounding box, area, circularity, eccentricity, etc.) are computed for content-based image retrieval (Veltkamp and Tanase, 2000). Once more, the high dependency on a good segmentation leads the researchers to avoid this kind of approaches when dealing with general purpose systems.

To overcome the segmentation problems, other approaches such as (Lipson et al., 1997) use predifined partitions of the image. Then, image classes are specified by means of photometric and geometric constraints (e.g. a beach scene is sketched as three partitions: sky, sea and sand). This approach deals with a fixed set of pattern configurations, thus is restricted to images of concrete scopes.

Our work consists in the development of a layout descriptor that try to overcome the weakness of the previous approaches and accomplishes this set of desirable characteristics:

- Capture the relevance of the parts that conform the image structure giving more weight to the exten-

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sive zones of the image than the details.

- Be easy to compute and do not relay to a rigid and computational intensive image segmentation procedure.
- Be applicable to any image without classification restrictions according to predefined layout templates.
- Be compact and indexable for retrieval proposes.

This paper is organized as follows: in the next section we expose the procedure to construct our layout descriptor and its related work; then, in section 3, we present some examples and results, and finally, in section 4, we resume the main conclusions of our work.

2 LAYOUT DESCRIPTOR

The layout information is a very descriptive cue for image description. Our work is focused in the construction of a a layout descriptor that encodes the position and relevance of the image zones. The algorithm follows three main steps:

First we construct a multi-layer representation that orders the regions by their saliency in relation to the whole image.

Then, the image zones are identified without requiring high quality segmentation by the means of the distance function on the edge information.

Finally, in every level of resolution, the relative positions of the zones are encoded using a triangulation process. The image layout is constructed as a histogram-based descriptor by joining the information of all analysis levels.

Next we describe the stages of the descriptor construction while we illustrate the process with an example. In Figure 4 we present all the intermediate images of the descriptor encoding steps.

2.1 Multi-resolution Image Representation

Linderberg (Lindeberg, 1996) observed that objects in the world appear in different ways depending on the scale of observation. He gives as a simple example the concept of a branch of tree which makes sense only at a scale from a few centimeters to at most a few meters, while it is meaningless to discuss the tree concept at the nanometer or kilometer level.

Besides this multi-scale properties of real-world objects, image retrieval systems need to cope with the complexity of unknown scenes and noise. This brings us to the conclusion that for a deep understanding of the image structure, multi-resolution image representation is necessary.

Witkin (Witkin, 1987) and Koenderink (Koenderink, 1984) introduced the idea of of generating coarser resolution images by convolving the original image with the Gaussian kernel. Thus, the resulting structure is known as linear, or Gaussian scale-space. For a given image $f(x,y)$, its linear (Gaussian) scale-space representation is a family of derived signals $L(x,y;t)$ defined by convolution of $f(x,y)$ with the Gaussian kernel

$$g(x,y;t) = \frac{1}{2\pi t} e^{-(x^2+y^2)/2t} \quad (1)$$

such that

$$L(x,y;t) = g(x,y;t) * f(x,y) \quad (2)$$

where $t = \sigma^2$ is the variance of the Gaussian.

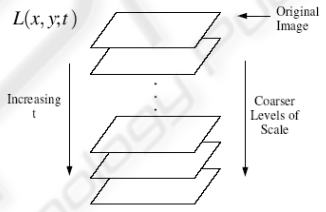


Figure 1: Scale-space image stack.

Such a representation is composed by the stack of successive versions of the original data set at coarser scales. It is assumed that, the bigger the scale, the less information referred to local characteristics of the input data will appear. We use this representation to analyze the image structures from low resolution to general information.

2.2 Image Zones Identification

In every resolution level we identify the zones that compose the image content according the contour information. Given an image $L(x,y;t)$, we apply the Canny operator to extract the edge information $E(L;t)$. We use the image edges as a binary representation from which we apply a distance transform function. The result is a map $D(E;t)$ that supplies each pixel of the image with the distance to the nearest edge pixel (Rosenfeld and Pfaltz, 1968). We understand the distance map as a topological surface where the valleys denote the limits of the image zones. To identify their positions we take as reference points the peaks of the ridges $P(D;t)$. Figure 2 shows and example of this process.

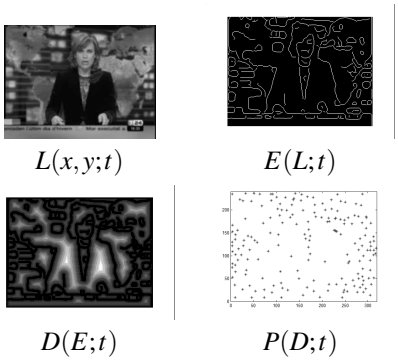


Figure 2: Image zone identification.

The image zone identification benefits from a procedure that does not require and intensive image segmentation. The image information can be easily extracted from the edges and it is not necessary that they conform closed regions.

2.3 Encoding of the Image Zone Spatial Arrangement

One we have identified the reference positions of the image zones we encode their spatial arrangement using a Delaunay triangulation. The Delaunay triangulation of a point set is a collection of edges satisfying an "empty circle" property: for each edge we can find a circle containing the edge's endpoints but not containing any other points. Delaunay triangulations maximize the minimum angle of all the angles of the triangles in the triangulation (Delaunay, 1934). These diagrams and their duals (Voronoi diagrams and medial axes) have been deeply studied and used in many common methods for function interpolation and mesh generation. Moreover, there are also many other ways in which this structure has been applied.

Gagaudakis (Gagaudakis and Rosin, 2003) made a set of experiments that identified the potential of measuring indirect shape using the Delaunay triangulation. He measured the performance of the image retrieval adding shape measures to the classical color histogram descriptors. They considered fourteen shape methods and test all their possible combinations, giving a total of over 16000 tests. The experiments where focused as a CBIR process applied on the frames of a video sequence. The tests conclude that the methods using the triangulation were involved in the most successful combinations of image feature descriptors.

Specifically, Tao (Tao and Grosky, 1999) described the shape of isolated objects using the spatial arrangement of the corner points. He applied a Delaunay triangulation on these feature points and analyzed the angular properties of the resulting triangles. The work introduced a novel method for image indexing although it failed to be very sensitive on the noise and the image variations.

In our work we encode the spatial arrangement of the image zones following a strategy similar to (Tao and Grosky, 1999) but taking as a feature points the reference positions of the image zones. Furthermore, the use of a multi-scale representation allow us to analyze the image from fine to coarse resolution and overcome the main drawback of the previous work.

For every image layer we construct a Delaunay triangulation $T(P;t)$ of the coordinate set $P(D;t)$. Then, a histogram is obtained by discretizing the angles produced by this triangulation and counting the number of times each discrete angle occurs in the image. Given the property that the three angles of a triangle sum 180 degrees, the histogram is built by counting the two largest angles of each individual Delaunay triangle. Figure 3 shows an example of the histogram construction $h(T;t)$.

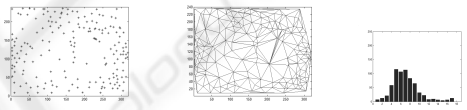


Figure 3: Layout encoding of a resolution level.

At this point, the layout information of an image is conformed by the set of the layout histograms $h(T;t)$ of each resolution level. Then, we combine all this information to construct the final image descriptor that we denote $H(\{h\})$. With this combination we want to reach two main objectives: obtain a compact descriptor and accentuate the multi-scale representation of the image zones. The steps we follow are the next: first we assemble the set of histograms $h(T;t)$ as the rows of a matrix. Then we compute the vertical and horizontal projections of this matrix and concatenate both projections in a single histogram. Finally, we normalize its content to one unit. The vertical projection enforces the layout of the dominant regions by adding repetitiveness of their spatial characteristics. Then the horizontal projection measures the amount of regions present in each resolution levels. This combination provides a considerably reduction of the information dimensions. Obtaining a compact descriptor is interesting for indexing applications and storage restrictions. The normalization process allows to define a closed range of dissimilarity measures. This fact is useful to study the similarity measure of the images in retrieval applications. Figure 5 shows graphically the computation of $H(\{h\})$.

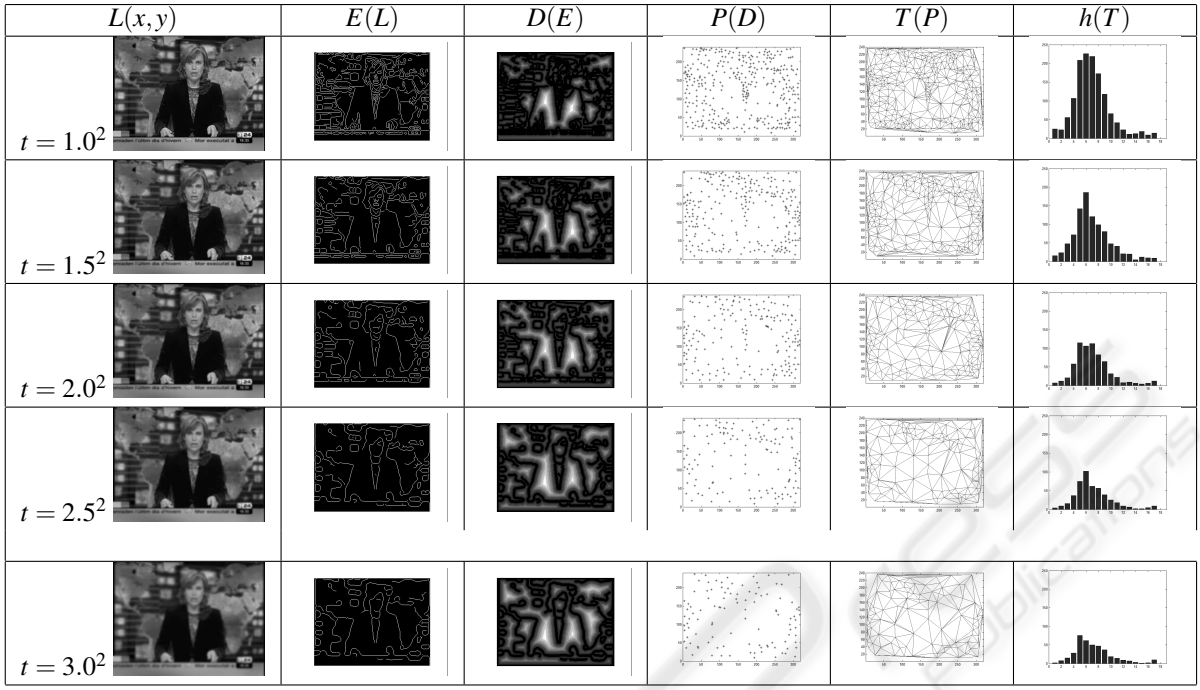


Figure 4: Example of the descriptor construction.

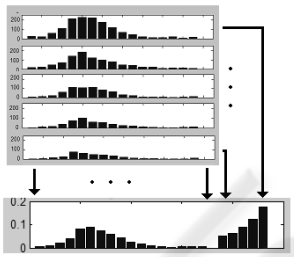


Figure 5: Computation steps of the layout descriptor $H(\{h\})$ from the histograms of every resolution level $h(T;t)$.

3 EXPERIMENTS AND RESULTS

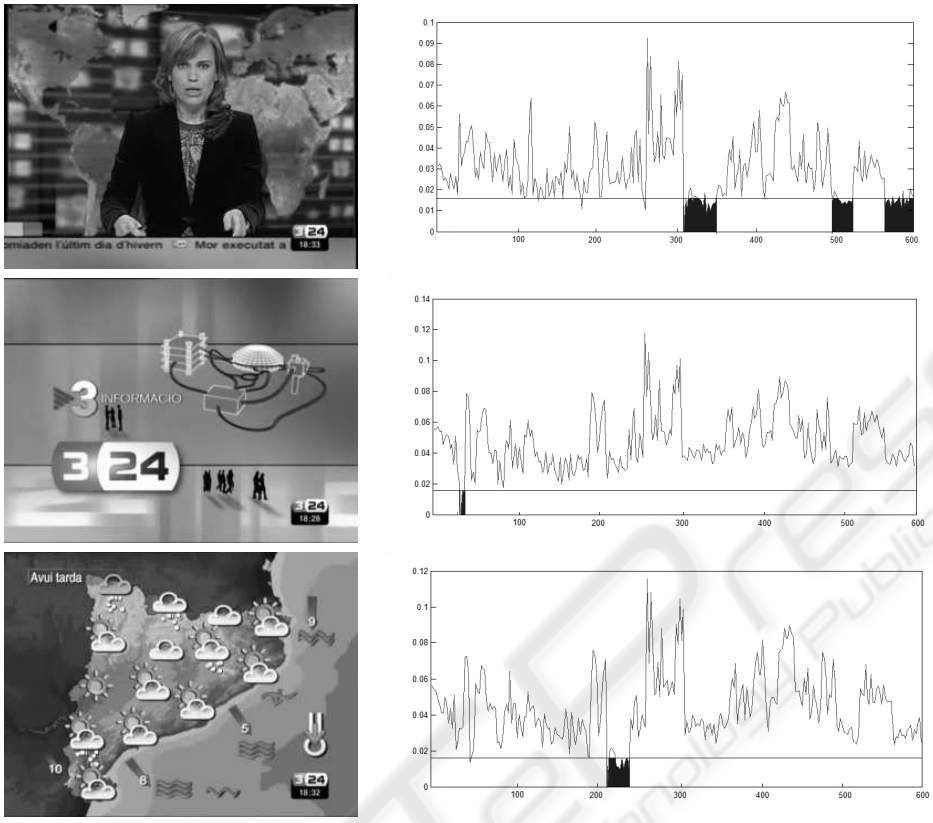
To test our work we have performed some initial experiments on images extracted form a video clip. We have captured the TV signal from a 24h news station called 3/24. The signal was captured two frames-per-second on a total of 5 minutes obtaining a total of 600 images.

First, for each test image we have computed our layout descriptor. Then, given a query image, the same feature vector is computed and compared to the feature vectors in the feature base.

For each test image we have computed our layout descriptor. We have experimentally set to 5 the number of scale-space layers codified by our representation approach, with σ parameter varying from 1.0 to 3.0. Nevertheless, for the rest of parameters we have based our work in the validation test of (Tao and Grosky, 1999). Thus, the number of histogram bins is set to 18 and the Euclidean distance is chosen as the similarity measure between two descriptors.

The similarity distance allows us to make a voting process along the time dimension of the video-clip and find out the appearance of certain characteristic scenes. Given a query image we observe the similarity of the video-frames. Knowing that $H(\{h\})$ has 23 bins and normalized content, the dissimilarity measures are in the range of $[0,\sqrt{2}]$. In the experiments, we observe that a group of consecutive images with dissimilarity distance minor than 0.0175 conform a retrieved scene. Setting an absolute threshold for similarity applications is always a hard task. Nevertheless, in this video browsing scheme we can benefit from the time consistence to reject and include exceptional false positives and negatives.

Figure 6 shows an example of detecting three characteristic scenes of a news program: the presenter, the program logo and the weather section. Figure 7 presents two examples of the retrieved scenes where we can observe the tolerance of the algorithm to slightly differences on the image content.



a) b)

Figure 6: Detection of the scenes in a video. a)Query image b)X axis represent the image of the video along the time. Y axes represent the dissimilarity value of the query image. A group of consecutive images which distance is minor than 0.0175 conform the retrieved scene. The first example retrieves three scenes, the second and third examples retrieve one scene.

a) b) c)

Figure 7: Two examples for the same image scenes. We can observe some differences as a) facial expressions, slightly different viewpoint b) reflection effects c) the image subheading and the dynamic weather symbols.

4 CONCLUSIONS

We have developed a descriptor that encodes the layout of an image using a histogram-based representation. The descriptor analyzes the image parts from a bottom-up direction using a multi-layer representation. These analysis enforce the representation of the image parts according to their saliency. Then we encode their relative positions using the properties of a Delaunay triangulation. The descriptor is easy to compute and can be extracted for general purpose in any image. The descriptor is compact, consist in a vector of 23 bins, and its content is normalized. These two properties make it suitable for image retrieval and indexing applications. Still in a very early evaluation stage, we have applied the descriptor in a video browsing application. Analyzing the similarity values of a given image we are able to detect the scenes along the clip that contain this kind of image. This work points out to promising results, so our immediate work is centered in a deeper validation.

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