Histogram of Radon Transform. A useful descriptor for shape retrieval

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Abstract

In this paper we present a new descriptor based on the Radon transform. We propose a histogram of the Radon transform, called HRT, which is invariant to common geometrical transformations. For black and white shapes, the HRT descriptor is a histogram of shape lengths at each orientation. The experimental results, defined on different databases and compared with several well-known descriptors, show the robustness of our method.

1 Introduction

Researches in shape descriptors have achieved a degree of maturity and extensive surveys on shape analysis can be found in [8, 16]. Two classes of feature descriptors are often encountered: those that work on a shape as a whole –called region-based descriptors– and those that work on the contours of the shape –called contour-based descriptors–. Usual contour-based descriptors include Fourier [5, 11, 16], curvature [3, 9] and histogram [2, 15] approaches. Since contour descriptors are based on the boundary of a shape, they cannot capture the internal structure of a shape. Furthermore, these methods are not suitable for disjoint shapes or shapes with holes because the inner boundary information is not available. Consequently, they are limited to certain kinds of applications. Region-based descriptors work on a shape as a whole taking into account all the pixels within a shape. Common methods are based on moment theory and geometric invariant methods [1, 13, 14], on multiresolution methods [10] and on Fourier transform [16]. Region-based methods are more suited to general applications. However, they are more computationally intense and most approaches need to normalize the image (centroid position, re-sampling, and re-quantization) to achieve common geometrical invariance. These normalizations introduce errors, sensitivity to noise, and thus inaccuracy in the recognition process.

In this paper, we propose a new region-based descriptor based on the Radon transform. We define a 2D histogram of the Radon transform (called HRT). For 2D black and white shapes, the HRT describes the repartition of lengths in each orientation. Experimental results show that the proposed method outperforms previous works on the Radon transform [12] and common shape descriptors. The paper is organized as follows. In section 2, we recall the Radon transform and the histogram definitions. Next, we present our new descriptor –section 3– and the matching process. In section 4, experimental results are given on different kinds of datasets and compared with well-known descriptors. Finally, we conclude and give the perspectives of our work.

2 Definitions

Radon transform: The definition of the continuous Radon Transform[4] is given by the integral of the image along straight lines parametrised by the slant ($\theta \in [0, \pi)$) and the distance to the origin of coordinates ($t > 0$):

$$Rf(t,\theta) = \int f(x,y)\delta_{\{x\cos\theta + y\sin\theta = t\}}(x,y)dxdy$$

Consequently, the Radon transform of an image is determined by a set of projections of the image along lines taken at different angles.

Histogram: Let be f a real function defined on a domain X: $f : X \to Y$. Besides, let us denote by $\#$ the cardinality of a set and by $|X|$ the size (length) of a domain X. Hence, the point-wise histogram of f is expressed by:

$$H(f)(y) = \frac{\#\{x \in X | y = f(x)\}}{|X|}$$

3 HRT descriptor

The HRT descriptor is defined as a matrix of frequencies computed on the Radon transform of an image aggregated by the angle parameter of the Radon transform. Thus, the HRT descriptor represents a 2D histogram of shape lengths at each orientation, in case of black and white shape images. More precisely, the HRT_f for a function f and for each orientation θ is:

$$HRT_f(y,\theta) = H(Rf(\cdot,\theta))(y), \quad \theta \in [0,\pi)$$

Observe that the sum of frequencies has to be one for each angle (orientation). The definition of the continuous HRT descriptor is invariant to shift and scaling objects. It is invariant since shifting objects only imply a shift on the radial parameter. Since the histogram is computed angle by angle, the distribution remains unchanged. Besides, invariance to scaling is also followed from the properties of the Radon transform. Scaling an image (a shape) gives rise to a scaling only in the radial parameter of the Radon transform. Again, the distribution of the histogram remains unchanged. However, the HRT descriptor is not invariant to orientation as the Radon transform is neither invariant to rotation. By the property of the Radon transform, a change of orientation causes a shift in the angular parameter of the Radon transform and for a rotation $\theta" = \theta' + \theta$:

$$HRT_f(y,\theta") = H(Rf(\cdot,\theta' + \theta))(y)$$

That is, a rotation of θ' from a initial position θ provides a shift of θ' in the HRT. Figure 1 shows the HRT descriptor for a same shape scaled, shifted and rotated. We can remark that only the rotation implies a shift of the histogram.

Matching: Classification strategies are not always well-suitable to tackle the matching step in information retrieval (IR) systems. They usually need predefined classes –in supervised approaches– or to be able to group data into several clusters –in unsupervised approaches–. Thus, a simple matching process based on the definition of a similarity measure and the retrieval of a ranking list of the top most similar objects is the common strategy applied.

As the HRT is not invariant to shape rotation, we have defined a rotation invariant similarity measure based on Euclidean distance: $||\cdot||_2$:

$$Sim(HRT_A, HRT_B) = \\ = \min_{\alpha\in[0,\pi)} ||HRT_A(y,\theta) - HRT_B(y,\theta+\alpha)||_2$$

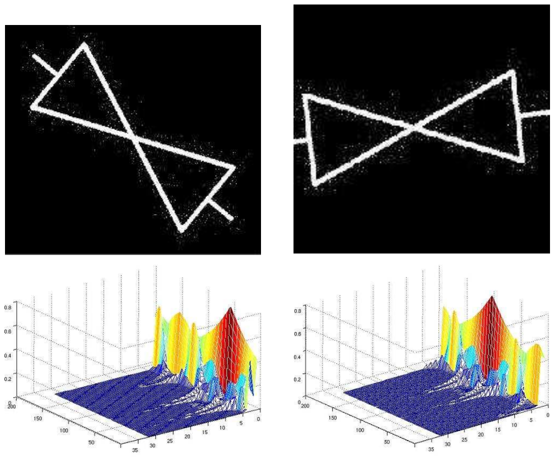


Figure 1. HRT **descriptor**

4 Experimental results

Performance of HRT descriptor have been evaluated for different datasets and compared to other descriptors commonly used in shape recognition problems and image retrieval applications. We have taken three different datasets: Shapes, Trademarks and Structural. Shapes[1] is composed of 18 classes of full shapes and 12 samples par class. Trademarks and Structural datasets have been constructed using the portal provided by the Epeires project[2]. Each dataset (Trademarks and Structural) is composed of 20 different classes of rotated, scaled and translated images. The number of samples for each class is not homogeneous and is of number of 300 for each dataset.

As it has been stated in the introduction, performances of shape descriptors depend on the application and, more specifically, on the geometry properties of shapes. Thereby, the used datasets have been chosen in order to cover a wide range of shape variabilities. Thus, Shape dataset is composed of connected full shapes, Trademarks dataset is composed of non-connected full shapes and Structural dataset is composed of non-connected wire shapes –see Fig. 2.

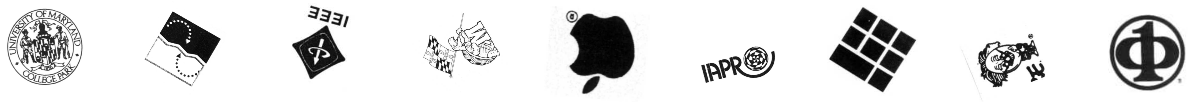
The descriptors used to compare to the HRT descriptor are: R-Signature[12], Angular Radial Transform (ART) [7], General Fourier descriptors (GFD)[16] and Shape Context (SC)[2]. All these descriptors are region-based except SC which is edge-based and have shown their robustness compared to others.

The average relevant rank (ARR) measure is used to evaluate the performance of the HRT descriptor compared to the others for the three datasets. Taking all the

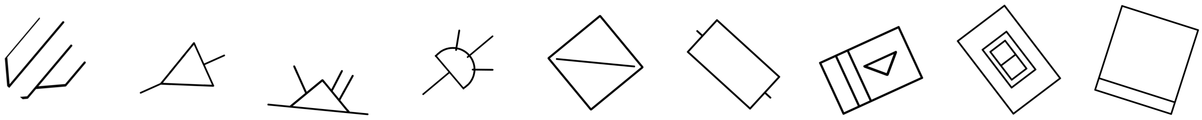
[1] http://www.lems.brown.edu/ des/

[2] http://www.epeires.org

(a) Shapes dataset



(b) Trademarks dataset



(d) Structural dataset

Figure 2. Examples of different datasets used in the evaluation

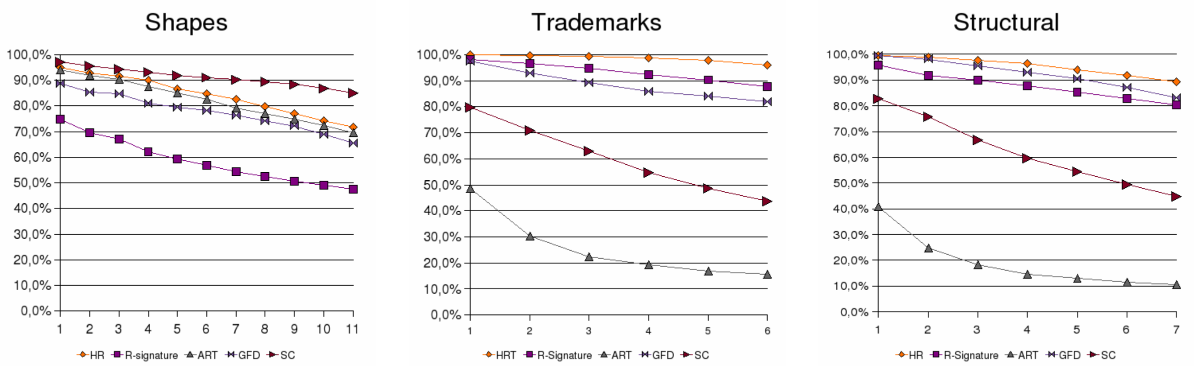


Figure 3. Average relevant rank

elements of the dataset as queries, the ARR compute the average of the corrected ranked in the k top positions (self-matching is excluded) –see Fig. 3–. In most cases, we can notice that the performance of HRT is better.

We have also tested our method on noisy data. The two previous datasets, Trademark and Structural, have been contaminated by a speckle noise designed by Kanungo model [6]. These noises are similar to noise obtained when a document is scanned, printed or photocopied –see Fig. 4–. Results are presented on Fig 5. We can remark that the performance of the descriptors drops down with the presence of noise but our descriptor HRT is still better for the trademark dataset and quite similar to GFD for the Structural.

5 Conclusion and Future Works

In this paper, we have presented a new descriptor based on the Radon transform. We have defined a 2D histogram of the Radon transform (called HRT) which is invariant to common geometrical transformations. For black and white images this descriptor gives the repartition on the angular length for a shape. We have shown on experimental results the robustness of the approach compared to others and whatever the kind of used dataset. Even if the method is promising, results with noisy images have addressed to the question whether the similarity measure (Euclidean distance) is well-suited or not. Therefore, in order to be more robust to noise, we want to explore other similarity measure. Also, future works will be devoted to reduce the size of the descriptor by including a multi-resolution decomposition framework.

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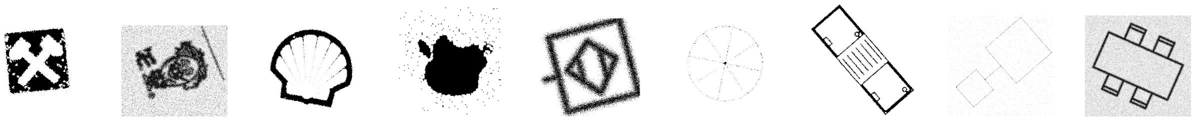

Noisy trademarks and Structural dataset

Figure 4. Examples of different datasets used in the evaluation

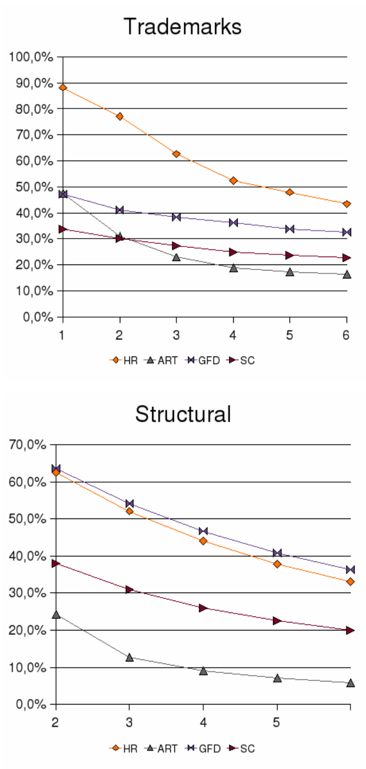

Figure 5. Average relevant rank for noisy datasets

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