Vision, Video, and Graphics (2005)
E. Trucco, M. Chantler (Editors)

A New Framework for Trademark Retrieval Based on Size Functions

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Abstract

We propose a new, effective system for Content–Based trademark retrieval, which involves Size Functions. Three different classes of shape descriptors are combined, for a total amount of 25 measuring functions. The evaluation has been performed on a database of 1182 trademark images, provided by the UK Patent Office.

1. Introduction

Dealing with trademarks is a challenging task for Content–Based Image Retrieval systems. First of all, there is an actual user need: since the number of registered trademarks in the world is enormous and rapidly growing, a performing system for automatic retrieval would save a lot of time when trying to avoid copyright infringement. But the challenge also comes out from images themselves: trademarks may contain one or multiple components, representing real objects as well as consisting of purely geometric or abstract shapes.

In this paper we propose a new approach to trademark retrieval, based on Size Functions, which are geometrical-topological descriptors, conceived for formalizing qualitative aspects of shapes. Size Functions seem to be particularly apt to this setting, since they have proven to be particularly useful for dealing with objects where no standard templates are available [VUFF93]. Moreover, their modularity allows us to incorporate in a unique framework different kinds of shape descriptions, through the choice of different measuring functions (see Section 3.2).

The rest of the paper is organized as follows. Section 2 provides a brief survey of existing works on this field. Section 3 describes our approach to trademark representation and matching. In section 4 we present the results obtained with our retrieval system on a database of about 1200 images, provided by the UK Patent Office. Some discussions in Section 5 will conclude the paper.

2. Literature review

Several research groups have been involved in facing the challenge coming out from automatic trademark retrieval. Kato's TRADEMARK system [Kat92] uses graphical feature vectors, including spatial distribution, spatial frequency, local correlation and local contrast, computed from normalized trademark images. Wu et al. STAR (System for Trademark Archival and Retrieval) system [WLM*96] involves Fourier descriptors and moment invariants extracted from manually segmented shapes. Principles deriving from Gestalt psycology are on the basis of ARTISAN project. The first prototype system [EGBS96] uses a combination of simple global features computed both from single image components and from families of grouped components; further versions [ERE03] show improvements in the grouping phase, the use of multiresolution analysis to cope with texture and noise, and the introduction of a variety of shape measures. Similar principles to ARTISAN give foundation to Alwis' work [AA99], which uses perceptual relationships between local features (such as co-linearism, co-curvilinearism, parallelism and end-point proximity) as well as features computed on closed contours of the images. In Ciocca and Schettini's system [SC99] moment invariants, edge directions and wavelet coefficients are used, while Kim and Kims [KKKK99] choose the magnitudes of Zernike moments as a feature set. Ravela and Manmatha [RM99] propose the use of two geometric features, the shape index and the local orientation of the gradient, computed from Gaussian derivatives of image intensity.

3. System description

Let us first recall the definition of Size Functions (SF's). The definition given below is slightly different from the one present in the literature [FL99]; differences arise only in pathological cases, of no interest in this research. We will then describe the set of measuring functions and the similarity score introduced to the scope of trademark retrieval.

3.1. Size Functions

Consider a continuous real-valued function $\varphi : \mathcal{M} \to \mathbf{R}$, called *measuring function*, defined on a subset $\mathcal{M}$ of an Euclidean space (often, it will be implicitely defined as the restriction of a function defined on the whole Euclidean space). The (reduced) *Size Function* of the pair $(\mathcal{M}, \varphi)$ is a function $\ell_{(\mathcal{M},\varphi)} : \{(x,y) \in \mathbf{R}^2 \mid x < y\} \to \mathbf{N}$.
For each pair $(x,y) \in \mathbf{R}^2$, consider the set $\mathcal{M}_x = \{P \in \mathcal{M} \mid \varphi(P) \leq x\}$. Two points in $\mathcal{M}_y$ are then considered to be equivalent if they belong to the same connected component of $\mathcal{M}_y$. The value $\ell_{(\mathcal{M},\varphi)}(x,y)$ is defined to be the number of the equivalence classes obtained by quotienting $\mathcal{M}_x$ with respect to the previous equivalence relation in $\mathcal{M}_y$.
A discrete version of the theory exists, which substitutes the subset of the plane with a graph $G = (V,E)$, the function $\varphi : \mathcal{M} \to \mathbf{R}$ with a function $\varphi\prime : V \to \mathbf{R}$, and the concept of connectedness with the usual connectedness notion for graphs.
Figure 1 shows a simple example of SF. In this case the topological space $\mathcal{M}$ is a curve, while the measuring function φ is the distance from point C.

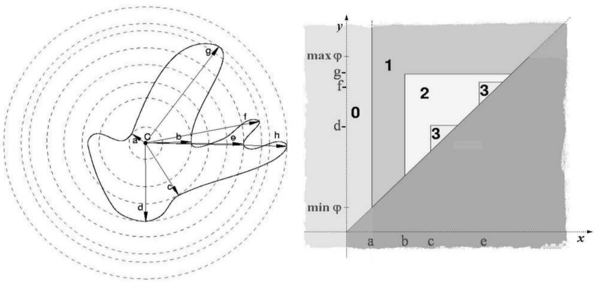

Figure 1: *Left: A pair $(\mathcal{M}, \varphi)$, where $\mathcal{M}$ is the curve depicted by a solid line, and φ is the distance from point C. Right: The corresponding reduced size function.*

As can be seen in Figure 1, SF's have a tipical structure: They are linear combination (with natural numbers as coefficients) of characteristic functions of triangular regions. That implies that each SF can be described by a formal linear combination of *cornerpoints* and *cornerlines*. Each distance between formal series naturally produces a distance between SF's. A detailed treatment of this subject can be found in [FL01]. Of the many available distances between formal series (see, e.g., [DFL99]), the one we use in this paper is the Hausdorff distance.
It is important to remark that SF's are easily and fast computable; see [d'Am00] for details.

3.2. Measuring functions

Three different and unrelated sets of measuring functions were implemented in our system.
The first set consists of sixteen distances from points. Let us fix a Cartesian reference frame (O, e_1, e_2) in the plane. From now on, points will be identified with their coordinate pairs. Let $p = (p_x, p_y) \in \mathbf{R}^2$. We define the measuring function $\varphi_P : \mathbf{R}^2 \to \mathbf{R}$ as $\varphi_P(x,y) = \mathrm{d}(p,(x,y))$ with d the Euclidean distance. Every input binary image is normalized (but without resolution loss) and translated so that its center of mass is taken to the origin of the reference frame. Therefore each measuring function φ_P is invariant by scale change and translation; as a consequence, the corresponding SF's turn out to be invariant by the same transformation group.
Here is the formal definition of the first set of measuring functions used in this research:

$$\Phi = \{\varphi_P | p = \frac{\overline{r}}{2}(cos(\overline{\alpha} + i\frac{\pi}{2}), sin(\overline{\alpha} + i\frac{\pi}{2}))$$

$$i = 1, \ldots, 4\} \cup$$

$$\{\varphi_P | p = \overline{r}(cos(\overline{\alpha} + i\frac{\pi}{4}), sin(\overline{\alpha} + i\frac{\pi}{4}))$$

$$i = 0, \ldots, 7\} \cup$$

$$\{\varphi_P | p = \frac{3}{2}\overline{r}(cos(\overline{\alpha} + i\frac{\pi}{4}), sin(\overline{\alpha} + i\frac{\pi}{4}))$$

$$i = 1, \ldots, 4\},$$

where the constants $\overline{r}$ and $\overline{\alpha}$ take value respectively 0.8 (all images are scaled with respect to average radius) and 0.349 (approximately corresponding to a 20 degrees phase-displacement).
The second set contains five measuring functions, each having a segment as domain. One of the five is a 'projection' of the image on the horizontal base segment: the whole image is fibered into a set of vertical pixel segments; for each of these, the number of black pixels contained in it is counted. The corresponding pixel of the horizontal base segment receives this number. The final measuring function is obtained by convolving these values, normalized dividing by the total number of black pixels, with a narrow Gaussian. The other four measuring functions are its variations built by projecting along the horizontal direction and along the three at $\pi/8$, $\pi/4$, $3\pi/8$.
The third set consists of four functions. One counts 'jumps' along the vertical direction. Again, the whole image is fibered into a set of vertical pixel segments; for each of these,

a counter is incremented each time two consecutive pixels of the vertical segment are of opposite colour. The corresponding pixel of the horizontal base segment receives this number of black-to-white and white-to-black jumps. Again, normalization (dividing by the maximum number of jumps) and convolution with a narrow Gaussian yields the final measuring function. In this case, the other three measuring functions are its variations built by counting jumps along the horizontal direction and along the two at 45 degrees.

3.3. Similarity assessment

Retrieval was performed combining in a single similarity score the Hausdorff distances coming out of the different SF's of the set. Since those distances do not share the same distribution, a normalization is called for; thus distances are normalized so that they have zero mean and unit variance. The final similarity score consists of an average of those normalized values, thus summarizing the contributions of the three descriptors.

4. Experimental results

4.1. Retrieval

In order to assess the ability of our system in retrieving similar trademarks, we decided to test it on a database of 1182 trademark binary images, coming from the UK Patent Office. 10 queries were submitted, for which we had similarity judgements provided by trademark officers.
The similarity score between two trademark images was given by the combination of the distances between the corresponding Size Functions, as described above in Section 3.3. The queries were then refined, adding some feedback capabilities: in order to give a different prominence to different measuring functions, according to their retrieval performance, for each of the three descriptors we computed a weight given by

$$\frac{1}{\sum_i R_i},$$

where R_i denotes the position of the i-th relevant image, among retrievals provided by that descriptor; images not occurring among the top 10% were assigned the maximum rank, i.e. the dimension of the database. Those weights were then used to re-order the lists of retrievals.
Notice that no preprocessing was performed on the images to remove holes or spots; this was done in order to test the resistance to noise of our system.

4.2. Performance evaluation

As stressed in several papers (e.g. [HS05], [LSLZ01], [MMSM01]), evaluation is a very critical issue for IR Systems. Apart from the problem of possessing a reliable and objective ground truth, all most common parameters have some drawbacks. A particular fault of several evaluation methods is that they don't take sufficiently well into account the position of the retrieved relevant objects within the scope (i.e. within the whole retrieved set). In what follows, we try to overcome this problem in two ways. First, we adopt the *normalized average rank* $\widetilde{Rank}$ introduced by [MMSM01]:

$$\widetilde{Rank} = \frac{1}{NN_{rel}} \left(\sum_{i=1}^{N_{rel}} R_i - \frac{N_{rel}(N_{rel}+1)}{2} \right),$$

where R_i is again the rank at with the i-th relevant image is retrieved, N is the dataset size, and N_{rel} is the number of relevant images for a given query. It is 0 for perfect performance and approaches 1 as performance worsens.
Second, we have also computed $P(k)$ and $R(k)$, respectively *precision* and *recall*, on the first k retrieved images, with $k = N_{rel}$, $2N_{rel}$, $3N_{rel}$, so adapting the scope to the (varying) number of relevant objects, rather in the line of normalizations supported by [HS05]. The *precision* and *recall* descriptors attempt to measure the effectiveness of the retrieval method measuring the ability of the system to retrieve relevant objects while discarding non relevant ones. Explicitly,

$$P(k) = \frac{NR(k)}{k} \qquad R(k) = \frac{NR(k)}{N_{rel}},$$

where $NR(k)$ is the number of relevant items among the first k retrieved.

	WLC	SLC	SMF
$\widetilde{Rank}$	0.080017	0.11908	0.180849
$P(N_{rel})$	0.621055	0.563939	0.399887
$P(2N_{rel})$	0.354907	0.310772	0.231875
$P(3N_{rel})$	0.249425	0.218207	0.165282
$R(2N_{rel})$	0.709814	0.621544	0.463751
$R(3N_{rel})$	0.748275	0.654621	0.495845

Table 1: *Evaluation of results. WLC: Weighted Linear Combination. SLC: Simple Linear Combination. SMF: Single class of Measuring Functions. Of course,* $R(N_{rel}) = P(N_{rel})$.

Table 1 gathers the average results for the weighted linear combination, for the simple linear combination, and for a single class of measuring functions. The number of relevant items N_{rel} for each queried trademark goes from a minimum of 4 to a maximum of 26. The reader should keep in mind that good ranks have low values, while good precision and recall have high scores. As can be seen, the evaluation parameters greatly improves from the combination of the three descriptors, with respect to the use of a single one.
The precision-recall graph of Figure 2 refers to the combined and the weighted similarity score. Figure 3 depicts the GRiP graph, plotting the value of precision=recall versus $-log_2(g)$, where the *generality* g is the ratio of the number of relevant items for each query (4 to 26) by the total size of the database (1182) [HS05].

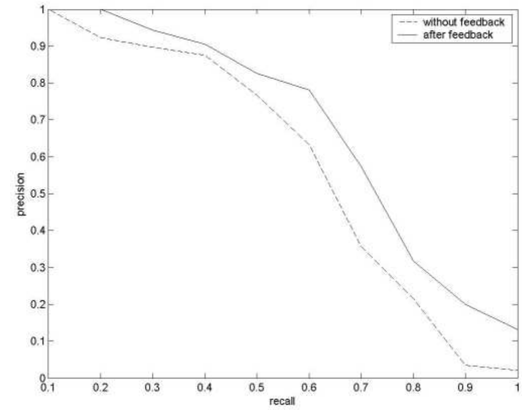

Figure 2: *Precision-recall graphs for the combined scores, before and after feedback.*

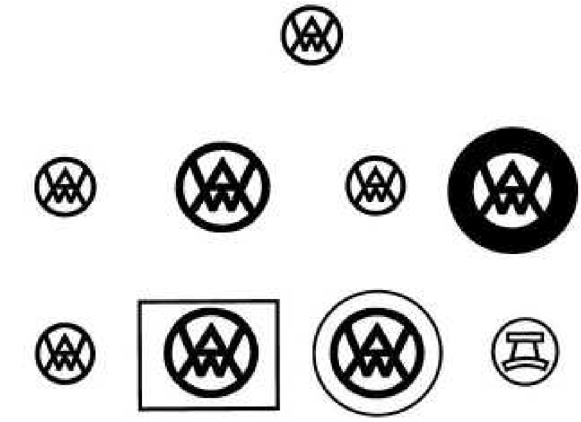

Figure 4: *A query example and the first eight retrievals.*

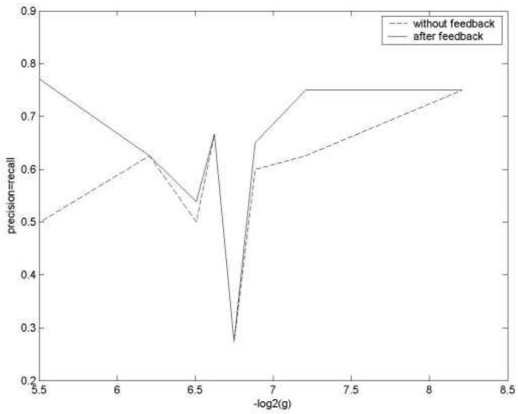

Figure 3: *GRiP graphs for the combined scores, before and after feedback.*

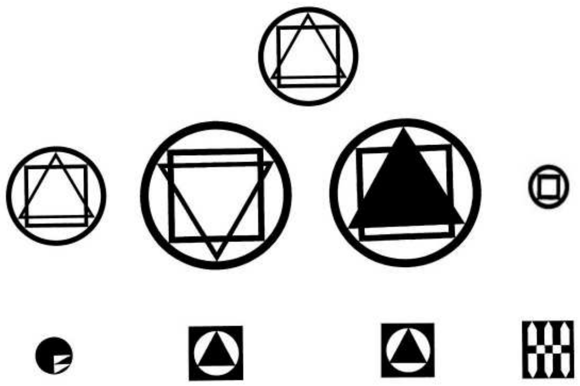

Figure 5: *A query example and the first eight retrievals.*

5. Discussions

5.1. Comments on the results

Figures 4, 5, 6 shows some retrieval exemples. For each query, the first 8 results are depicted; the query has always been retrieved as the first one, as a confirm of the robustness of the system.

As can be seen (e.g. in Figure 4), our system has proven to be resistent to noise: Noisy or different in size instances of the same trademark are always retrieved within the first positions, altough sometimes they show lowest rank with respect to other relevant images.

Figure 5 shows the persistence of the same shapes, i. e. triangles and circles, in the first retrieved objects, apart from the clear false positive in 8th position; the square inside the circle has not been judged relevant by the UK trademark officers, and probably is not, but, at a first glance, it may be perceived as similar.

Figure 6 shows that images consisting of two instances of the same shape may be perceived as similar to other images sharing the same structure (mainly projections measuring functions 'see' that kind of structure, while, e. g., jumps measuring functions tend to perceive two instances of the same object as a single one, due to the choosen normalization); this can be an advantage (see the 4th or the 5th ranked object), but also a drawback (as for the 6th or the last one of the list).

Browsing the actual outputs of the queries for each measuring function is very interesting. A single descriptor is not very effective by itself, due to the presence of many false positives among the first retrieved objects; what is interest-

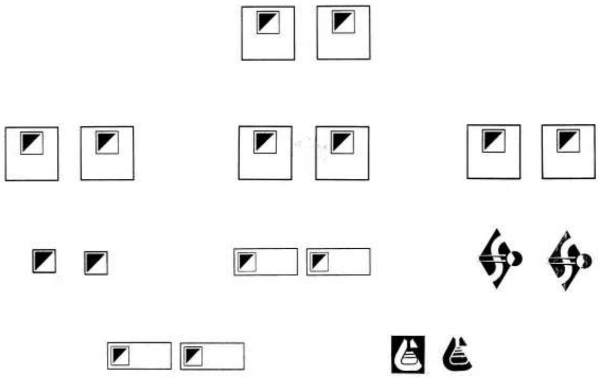

Figure 6: *A query example and the first eight retrievals.*

ing is that the classification of relevant items is quite different for each class of measuring functions, as they were looking at trademarks from different points of view: This ensures that the combination of results gives a reliable improvement to the ordering of retrievals. Figure 7 shows the different orderings of relevant objects in response to the same query, obtained by the three different classes of measuring functions; notice, e. g., that 'jumps' actually perceive as similar the image in which the contour of the object is thicker (the one with rank 10), since the number of jumps does not change, while 'projection' is clearly mistaken by the same image.

5.2. Conclusions

We have presented a new system for Content–Based trademark retrieval, based on the use of Size Functions as shape descriptors.
Three classes of measuring functions, namely distances, projections and jumps, have been involved, showing resistance to noise and a promising effectiveness in retrieval on a database of 1182 trademark images.
We are currently investigating the possibility of introducing new measuring functions, in order to have a more complete description of shapes.

Acknowledgements

Work performed within the activity of ARCES "E. De Castro" and of CIRAM, University of Bologna, under the auspices of INdAM-GNSAGA and of the University of Bologna, funds for selected research topics.
The authors wish to thank Dr. John Eakins at the University of Northumbria, Newcastle, and the UK Patent Office for providing the trademark database.

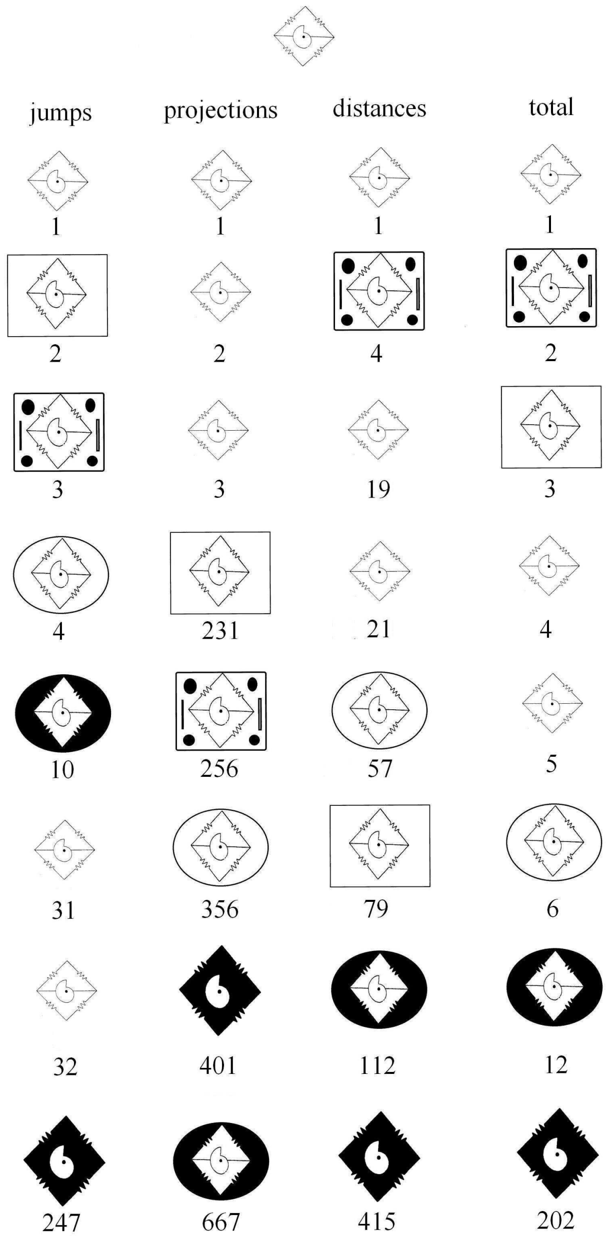

Figure 7: *A query and its relevant images. The first three columns are related to the three different classes of measuring functions, respectively jumps, projections and distances; the last column shows the final ordering after the weighted averaging. For each column, the results are arranged according to their similarity score with respect to the query model, from top to bottom; the numbers represent the rank at which the corresponding images have been retrieved. The normalized weights computed here were 0.483 for jumps, 0.103 for projections and 0.414 for distances.*

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