# Dynamic Selection Feature Extractor for Trademark Retrieval

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**Abstract.** The paper contributes to the CBIR systems applied to trademark retrieval. The proposed method seeks to find dynamically the best feature extractor that represents the trademark queried. In the experiments are applied four feature extractors: Concavity/Convexity deficiencies (CC), Freeman Chain (FC), Scale Invariant Feature Transform (SIFT) and Hu Invariant Moments (Hu). These extractors represent a set of classes of features extractors, which are submitted to a classification process using two different classifiers: ANN (Artificial Neural Networks) and SVM (Support Vector Machines). The selecting the best feature extractor is important to processing the next levels in search of similar trademarks (i.e. applying zoning mechanisms or combining the best feature extractors), because it is possible restrict the number of operations in large databases. We carried out experiments using UK Patent Office database, with 10,151 images. Our results are in the same basis of the literature and the average in the best case for the normalized recall ($R_n$) is equal to 0.91. Experiments show that dynamic selection of extractors can contribute to improve the trademarks retrieval.

**Keywords:** Dynamic selection · Feature extractor · ANN · SVM

## 1 Introduction

Trademarks are used as marketing tools, communicating a certain assurance of quality and innovation which the companies seek to promote and maintain [7]. They are important reputational assets, and your violation can have serious consequences [11].

In order to maintain the integrity and visibility of their trademarks, companies constantly search in the web and the media (magazines, newspapers, videos, among others) existence of trademarks similar to yours. For Abe *et al.* [4], the labor and cost associated with this effort increase every year. However, these concerns should be considered from the beginning of the process of registering a new trademark [11], verify conflicting with a trademark already registered, as well as avoid infringement of copyright. Trademark retrieval is highly complex task, due to the diversity of form and abstract elements that a trademark has. Thus, recognition systems need to have mechanisms to ensure efficiency at retrieval task.


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A pattern recognition problem can involve a number of patterns with each class consisting of various features. For Aires *et al.* [9] is very hard to a single feature extractor solves the complexity and reaches the best solution. Each feature extractor looks at the image for different types of information, such as: topological, geometric, texture, edge, and others. However, each represents the image differently, and often the representation of this image by a particular extractor achieves more accurate results than other features extractors. Thus, using a lot of extractors allow the system to determine an extractor that highlights features that best represent the various information in the image and can differentiate it from the other images in the database.

This work show the CBIR (Content-based Image Retrieval) systems applied to trademark retrieval, seeking to a classifier can contribute by finding the feature extractor that best represents the elements of the trademark required.

The paper is organized as follows. Section 2 presents the concepts and related works to CBIR Systems. Section 3 presents the feature extractors, classifiers and the baseline system. The experiments and results are summarized in the Sect. 4. Finally, the Sect. 5 discusses the experimental results and present the conclusion and future works.

## 2 Related Works

Because of economical relevance of trademarks the company's request intelligent image analysis systems [8]. In this way, such intelligent systems start the process by registering a new trademark. However, all of these applications need to handle great amount of images. Thus, this kind of system is a challenge for many researchers.

The work presented by Kumar *et al.* [12] considered the three most important systems for trademark retrieval: Artisan, Star, and. Trademark Systems. Different methodologies and approaches have been applied by these systems. The Artisan System proposed an approach taking into account principles of human perception, which consists of some abstract geometric designs [1]. Star System applied CBIR techniques, including the Fourier descriptors, grey level projection, and moment invariants [14]. The Trademark System applies graphical feature vectors (GF-vector) to describe the image and calculate the similarity based on human perception [4]. For Anuar *et al.* [7] these three systems are very important and significant researches on trademarks.

The study presented by Shaaban *et al.* [13] presented the approach for retrieving trademark based on integrating multiple classifiers; the idea is speed up the retrieving process and to improve retrieving accuracy. The system applied three feature extractors: Invariant Moments; Decomposition in Singular Values (SVD - Singular Value Decomposition) and Discrete Cosine Transform (DCT - 2D Discrete Cosine Transform). For [13] feature extraction is the most important step in these kind of systems; obtaining good results in the selected features to utilize them in the classification stage.

Haitao *et al.* [5] extracted the features based on the contour of the image using Fourier Moments. In the experimentation was applied SVM model to solve the problems of poor generalization performance, local minimum and over fitting. In addition, kernel function was applied in SVM maps data set linear inseparable to a higher dimensional space where the training set is separable. For [5] this is the reason for the SVM classifiers are widely used in pattern recognition.

Consider the popularization and increasing use of the deep learning methods, well-known Convolutional Neural Network (CNN), Aker *et al.* [15] applied these models to the trademark retrieval problem. Models were tested using a large scale trademark dataset. Some solutions were presented, such as, fine-tuning, distance metric learning, using CNN features locally, and making them invariant to aspect ratio of the trademark.

As presented before, several authors [12, 13, 5, 15] have investigated the similarities between trademarks. However, the development of retrieval systems is challenged because the high degree of difficulty to find features extractors that may represent the trademark queried in a way that distinguishing the others trademarks in large database (with a high degree of dissimilarity).

In this paper, our efforts were to determine which feature extractor best represent a trademark. In the experiments carried out we have class of features extractors and for classification we test four ANNs Class Modular and a SVM.

## 3 Baseline System

The experimental protocol uses as input a 256 grey-level image. Then, a preprocessing step is applied, which is composed to binarization (OTSU) and bounding box definition. The feature set is based on four methods of extraction. Two methods contour-based: Freeman Chain Code (FCC), Concavity/Convexity deficiencies (CC), and two methods region-based: Scale Invariant Features Transform (SIFT) [6] and Hu Invariant Moments (Hu). Matching of the similarities was calculated by Euclidian distance. The best results of Top-1% were compared with [1] and [3].

### 3.1 Database

We use the UK database Patent Office that belongs to the Intellectual Property Office (IPO) from United Kingdom (http://www.ipo.gov.uk) to perform our experiments. This database contains 10,745 images of trademarks, all in gray-levels. The experiments

**Table 1.** Truth set

| No. | TM | Similar | No. | TM | Similar | No. | TM | Similar | No. | TM | Similar |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **01** | | 25 | **06** | | 17 | **11** | | 09 | **16** | | 11 |
| **02** | | 15 | **07** | | 10 | **12** | | 15 | **17** | | 20 |
| **03** | | 11 | **08** | | 19 | **13** | | 12 | **18** | | 09 |
| **04** | | 09 | **09** | | 24 | **14** | | 12 | **19** | | 22 |
| **05** | | 09 | **10** | | 10 | **15** | | 16 | **20** | | 12 |
| | | | | | | | | | | Total | 287 |
| | | | | | | | | | | Total Overall (287+ 20 test) | 307 |

were carried out using a set of 20 image queries selected by experienced trademark examiners from UK Patent Office. The 20 image queries are shown in Table 1.

## 3.2 Features Extractors

In this section we will briefly present the feature extractors applied in this work. More details can be found in [9].

**Concavity/Convexity Deficiencies (CC)**
The Concavity/Convexity deficiencies feature set puts on evidence the topological and geometrical properties of the shape to be recognized and is computed by labeling the background pixels of the input images. The idea of concavity/convexity deficiencies is check for each background pixel in the image; we search in four-directions: North, South, East, and West. When black pixels are attain in all directions, we verify at four auxiliary directions in order to confirm if the current white pixel is really inside a closed contour. The entire and definitive symbols were adapted to trademark retrieval, and then we have 24 different symbols [9]. Figure 1a presents the labeling process of background pixels from a trademark query.

**Freeman Chain Code (FC)**
Chain codes are used to represent borders of objects, through a sequence of straight line segments of specified length and direction [9]. Figure 1b presents Freeman Chain Code from a trademark query.

**Scale Invariant Feature Transform (SIFT)**
Lowe [2] presents a framework to extracting distinctive invariant features from images and shows that it can be used to perform matching between different views of an object or scene. The features are invariant to image scale and rotation, and provide robust matching across a substantial range of affine distortion, noise, and illumination changing's. Lowe [2] presents four important stages to generate the set of image features: (1) scale-space extreme detection; (2) key-point localization; (3) orientation assignment; (4) key-point description.

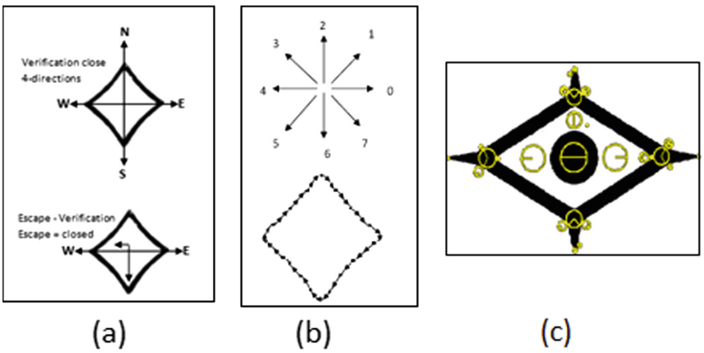


**Fig. 1.** (a) Concavity/Convexity deficiencies (b) Freeman Chain Code (c) SIFT in trademark database UK

This approach is widely applied in many researches [8, 11, 15] for retrieval objects in images databases. For this reason, we tested SIFT in our experiments. Figure 1c shows SIFT features extracted from a trademark contained in the UK/IPO database.

**Hu Invariant Moments (Hu)**
The seven moments proposed by Hu are widely used in image processing because of the robustness to image translation, scale and rotation transformation. These moments are represented by seven equations nominated as Hu invariant moments and Hu moments. Moment is a robust technique for decomposing an image into a finite set of invariant features. In practical terms, the use of Moments for image recognition requires the selection of a subset of moment values that contains enough information to characterize each image only [9].

### 3.3 Dynamic Selection

It was necessary to define a strategy that would be able to dynamically select the best extractor. For this task, experiments were performed using two classifiers: Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Details on the construction of these classifiers are contained in the following sections. Both classifiers were trained and tested based on "truth set" contained in the UK Patent Office database [17], presented in Table 1.

**Artificial Neural Network**
Artificial Neural Networks based on supervised learning have a set of input variables and an expected output set. ANN compares the output value to the desired value, making corrections to the model so that it encounters an acceptable error. After the training step, a new input set unknown can be presented to ANN and its task is to correctly classify this new class.

Based on the individual results presented in Table 2 of Sect. 4.1, the ANN training and validation sets were constructed. Neural network training was performed using four (4) MLP (Multi-Layer Perceptron) networks with hidden layers, considering that the number of neurons in the hidden layer is the half number of neurons in the input layer. The number of training epochs is variable according to the extractor used in each ANN, such values were obtained observing the learning curve from JNNS during the training. The learning algorithm used was Back Standard Propagation, with learning parameter 0.2. The weights were randomly initialized with values between −1 and 1.

The Fig. 2 presents an overview of the building of ANN under the premise of making Multiple Classifiers. Thus, each trained ANN is specialized in recognizing a class of extractor. Each ANN has as output values between 1 and 0; '1' represents "recognized" image and '0' represents "unrecognized" image for the evaluated extractor class. Given a query trademark, information is extracted applying all four extractors described in Sect. 3.2. Then the features vectors are normalized and sent to the respective ANN (Fig. 2).

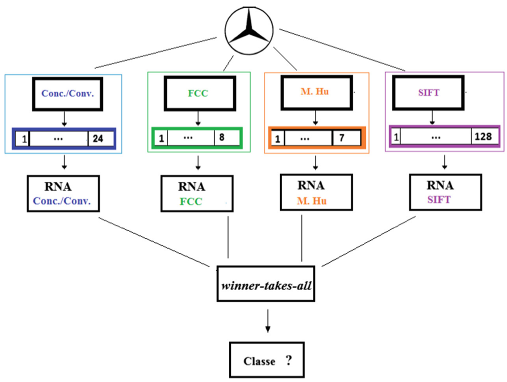


**Fig. 2.** ANNs multiple classifiers.

### SVM

The SVM classifier used in this work was built by LIBSVM tool widely used and available in [16]. For building the SVM classifier, it is necessary to define training and test sets. These sets were created using information from the 307 trademark images contained in the “truth set” (Table 1). The SVM training set, which has 287 images, was constructed based on the individual results presented in Table 2 of Sect. 4.1, such as the methodology used for the construction of the ANN sets. Unlike the ANNs, only one SVM classifier was built for the classification problem. The composition of the characteristics vector is accomplished by the union of the feature vectors of the four extractors and the class to which each trademark belongs, as shown in Fig. 3.

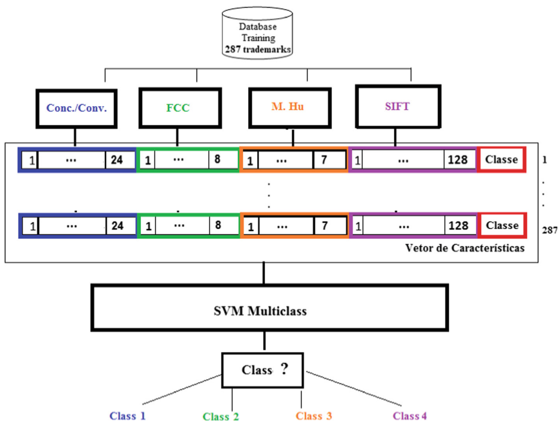


**Fig. 3.** SVM classifier.

The Fig. 3 shows the composition of the SVM Multiclass training set used in the experiments, being trained and tested for the four classes representing the four extractors applied to the Model: class 1 - Concavity/Convexity Deficiencies - CC (dimension vector 24), class 2 - Freeman Chains - FCC (vector of dimension 8), class 3 - Invariant Moments of Hu (vector of size 7), and class 4 - SIFT extractor (dimension vector 128). The feature vector has a total size equal to 167. The 20 query images were inserted only in the test database. As a final result, SVM indicates the best extractor to be applied to the trademark query.

### 3.4 Matching and Measure of Retrieval

The similarity calculation between the trademarks is performed through the Euclidean distance of the feature vectors. To evaluate the results the trademarks retrieval, we used two measures usually applied in any CBIR system that generates output in ranked order: Normalized Recall $R_n$ and Normalized Precision $P_n$ [1]. The system retrieval performance, in return to a query, is 0 (worst case) to 1 (best case). Normalized Recall and Precision are defined by following Eq. (1) and (2).

$$R_n = 1 - \frac{\sum_{i=1}^{n} R_i - \sum_{i=1}^{n} i}{n(N-n)} \tag{1}$$

$$P_n = 1 - \frac{\sum_{i=1}^{n} (\log R_i - \sum_{i=1}^{n} (\log i)}{\log\left(\frac{N!}{(N-n)!n!}\right)} \tag{2}$$

Where $R_i$ is the rank at which relevant trademark, $i$ is actually retrieved, $n$ is the total number of relevant trademarks, and $N$ is the size of the whole trademark database.

## 4 Experimental Results

The proposed method to the dynamic classification of the feature extractor is presented in Figs. 2 and 3. The matching among the query image and the images in the database is performed to calculate the similarity using Euclidian Distance, and an overview of the complete method is presented in Fig. 4. At the end, a ranking of the Top-100 of the images most similar to the query image is presented as result.

### 4.1 General Results of Features Extractors

In this section a comparison is made between the results of all extractors used in the experimentations. The best results are presented in Table 2, highlighting the best $R_n$ rate for each trademark contained in the true set (Table 1). Table 2 is important because the individual results of each feature extractor were used to define training and validation sets to be used by the classifiers (as discussed in Sect. 3.3).

We observe in Table 2 that by selecting the extractor that best represents the trademark, it is possible to improve the recovery rate. Also, we did not combine feature extractors to increase the $R_n$ rate. Considering that the features extractor is an important component in CBIR systems to obtain good results, this knowledge allows to design

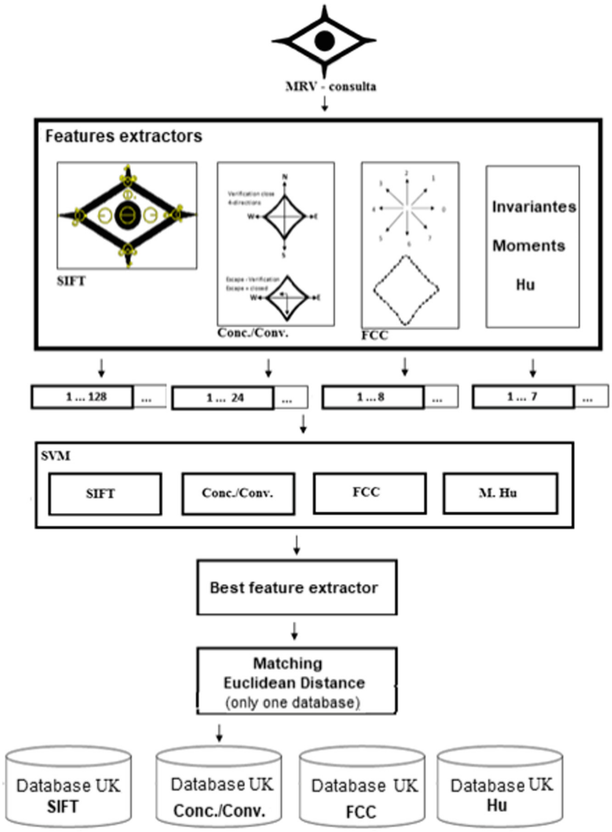


**Fig. 4.** System overview.

strategies to improve its performance in the recovery of similar trademarks (for example, applying zoning mechanisms or combining the best feature extractors).

## 4.2 Results ANNs

Four ANNs were constructed, each one specialized in one of the four features extractors. The goal is to obtain a 'vote' or score from each one ANN for each trademark queried. By means of the Majority Rule, the class of extractor that trademark belongs to is determined, that is, the best extractor to be used for the trademark in question was determined. This task is important to maximize the obtained results. The Table 3 presents the votes of each ANN for the 20 trademarks queried; the 'Best' extractor is presented in Table 2.

We can observe at Table 3 that 14 trademarks were able to be classified correctly in their extractor classes. Therefore, 6 images did not obtain the expected results and, for 4 images, the second largest vote ranks correctly ( , , , ). This demonstrates that the Majority Rule strategy could be replaced so as to also consider the

**Table 2.** Best feature extractor - $R_n$

| TM | CC | FCC | SIFT | Hu | Best | TM | CC | FCC | SIFT | Hu | Best |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0,91 | 0,79 | 0,89 | 0,91 | 0,91 | | 0,68 | 0,47 | 0,67 | 0,87 | 0,87 |
| | 0,90 | 0,79 | 0,93 | 0,81 | 0,93 | | 0,68 | 0,77 | 0,94 | 0,57 | 0,94 |
| | 0,74 | 0,79 | 1,00 | 0,64 | 1,00 | | 0,65 | 0,86 | 0,98 | 0,81 | 0,98 |
| | 0,96 | 0,80 | 0,89 | 0,77 | 0,96 | | 0,82 | 0,79 | 0,96 | 0,58 | 0,96 |
| | 0,85 | 0,89 | 0,99 | 0,50 | 0,99 | | 0,66 | 0,85 | 0,65 | 0,48 | 0,85 |
| | 0,85 | 0,39 | 0,76 | 0,70 | 0,85 | | 0,48 | 0,62 | 0,87 | 0,44 | 0,87 |
| | 0,68 | 0,89 | 0,60 | 0,59 | 0,89 | | 0,76 | 0,45 | 0,58 | 0,59 | 0,76 |
| | 0,95 | 0,58 | 0,93 | 0,63 | 0,95 | | 0,83 | 0,89 | 0,45 | 0,59 | 0,89 |
| | 0,75 | 0,73 | 0,81 | 0,30 | 0,81 | | 0,75 | 0,97 | 0,61 | 0,52 | 0,97 |
| | 0,79 | 0,90 | 0,42 | 0,74 | 0,90 | | 0,89 | 0,85 | 0,96 | 0,82 | 0,96 |
| | | | | | | Average | 0,78 | 0,75 | 0,79 | 0,64 | 0,91 |
| | | | | | | SD | 0,12 | 0,17 | 0,19 | 0,16 | 0,06 |

second largest vote. The trademark ( ) that was supposed to be classified belonging to the class of extractor Moments de Hu, was not successful. This fact is due to the amount of examples of this trademark contained in the truth set (only nine). It is important to note that only this trademark obtained better results with Hu Moments, resulting in a small set of trademarks for the training, validation and testing set, this amount was insufficient to solve this task.

The results obtained by the ANNs were not enough to solve the classification to determine the best extractor to be used by queried trademark. In order to obtain better results, experiments were performed applying SVM.

### 4.3 Results SVM

The Support Vector Machines (SVM) was developed with the purpose of performing classification tasks, being successfully used in pattern recognition applications [5, 6, 10].

In order to evaluate the performance of SVM in the classification of extractors, comparing with the results obtained by ANNs presented in Sect. 4.2, a SVM Multiclass was constructed. The features vectors of each extractor were combined (juxtaposed) in a single feature vector. This vector has a dimension equal to 167, that is: 128 features obtained by the average of the SIFT key points, 24 features of Concavity and Convexity, 8 features of Freeman Chains Code and 7 features of Hu Moments. Two sets were constructed: training and testing. Table 4 shows the results obtained from the trademarks contained in the test set.

**Table 3.** Vote 4 (four) ANNs

| Trademark | 1o. | 2o. | Best | Trademark | 1o. | 2o. | Best |
|---|---|---|---|---|---|---|---|
| | CC | SIFT | CC | | CC | SIFT | HU |
| | SIFT | M. Hu | SIFT | | SIFT | M. Hu | SIFT |
| | SIFT | CC | SIFT | | SIFT | FCC | SIFT |
| | CC | M. Hu | CC | | SIFT | M. Hu | SIFT |
| | SIFT | FCC | SIFT | | FCC | M. Hu | FCC |
| | CC | SIFT | CC | | SIFT | CC | SIFT |
| | SIFT | FCC | FCC | | CC | FCC | CC |
| | FCC | CC | CC | | SIFT | FCC | FCC |
| | SIFT | M. Hu | SIFT | | SIFT | FCC | FCC |
| | CC | M. Hu | FCC | | SIFT | M. Hu | SIFT |

**Table 4.** SVM multiclass

| TM | Predict | Table 2 | $R_n$ Best | TM | Predict | Table 2 | $R_n$ Best |
|---|---|---|---|---|---|---|---|
| | CC | CC | 0,91 | | HU | HU | 0,87 |
| | SIFT | SIFT | 0,93 | | SIFT | SIFT | 0,94 |
| | SIFT | SIFT | 1 | | SIFT | SIFT | 0,98 |
| | CC | CC | 0,96 | | SIFT | SIFT | 0,96 |
| | SIFT | SIFT | 0,99 | | FCC | FCC | 0,85 |
| | CC | CC | 0,85 | | SIFT | SIFT | 0,87 |
| | FCC | FCC | 0,89 | | CC | CC | 0,76 |
| | CC | CC | 0,95 | | FCC | FCC | 0,89 |
| | SIFT | SIFT | 0,81 | | FCC | FCC | 0,97 |
| | CC | FCC | 0,79 | | SIFT | SIFT | 0,96 |
| | | | | | Average | | 0,91 |
| | | | | | SD | | 0,06 |

In the results presented in Table 4 we can observe that the SVM was able to classify the trademarks better in relation to the results obtained by the ANNs. Of the 20 trademarks in the test set, 19 trademarks were classified correctly. The trademark ()

did not obtain the expected result, its class should be FCC, but was classified as Concavity/Convexity. This fact also occurred for ANNs.

Based on 20 trademarks from the test set, only one trademark presented confusion (Table 4). However, this result does not affect the General Average of the best extractor for $R_n$, since the difference between the results obtained by the extractors is 0.1, Concavity/Convexity obtained $R_n$ = 0.79 and FCC obtained $R_n$ = 0.90. These results confirm that SVMs are successful in pattern recognition systems. According to [6], the SVMs are efficient in relation to speed and complexity. This method equates the minimum search of a convex function, that is, without local minimums. Thus, many problems that occur in ANNs and decision trees are eliminated. This observation may explain the good results obtained by the SVM in relation to the ANNs.

**Table 5.** Comparative results average overall

| Authors | $R_n$ | $P_n$ |
|---|---|---|
| Our method – best extractor | 0.91 | 0.75 |
| Eakins et al. [1] | 0.89 | 0.67 |
| Cerri et al. [3] | 0,81 | 0,56 |

## 5 Discussion and Conclusion

Select an extractor features that best represents the trademark reduces the search in databases. The features extracted are concatenated in a single vector only when sent to SVM (167 features). When the SVM selects which extractor use, the search in the database is restricted to number of features of best extractor, it reduces the cost, because the system has fewer values to compute between the queried trademark and the 10,151 trademarks of the database.

We can observe in Fig. 4 a trademark query, a feature extraction by four proposed features extractors, the features being sent to SVM, the matching with the other images of the database is restricted to database referring to the extractor indicated by SVM. The trademark () obtained the best results with the Concavity/Convexity extractor, so the matching will only be performed in the database of the images with the Concavity/Convexity features, only 24 features are used to perform the matching.

Additionally, zoning mechanisms can be applied considering only the features extractor defined by the SVM. Zoning mechanisms were applied in trademark retrieval in reference [11]. More, interesting experiments can be performed combining the best features extractors.

The Table 5 compares our results with the literature. The references [1] and [3] also used in their experiments the database of UK Patent Office. However, [1] and [3] do not use any classifiers in their experiments. It is important to observe that in this work and in [1] and [3] the feature extractors used are different. However, the Matching (Euclidian Distance) and the Measure of Retrieval $R_n$ and $P_n$ (presented in Sect. 3.4) are the same. The rates compared in Table 5 relate to the recovery rate of the trademarks contained in the true set (Table 1).

We understand that using SVM to classify the feature extractors made it possible to improve trademark retrieval rates (Table 5) and additionally reduces the cost (making fewer comparisons) during the retrieval task in large databases.

So, our results are better to those found in the literature and it convinced us to carry on the research, including experiments using Deep learning [15] and increasing the number of query images. These observations are opening the way for new interesting directions of research.

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