A Relevant Visual Feature Selection Approach for Image Retrieval

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Abstract: Content-Based Image Retrieval approaches have been marked by the semantic gap (inconsistency) between the perception of the user and the visual description of the image. This inconsistency is often linked to the use of predefined visual features randomly selected and applied whatever the application domain. In this paper we propose an approach that adapts the selection of visual features to semantic content ensuring the coherence between them. We first design visual and semantic descriptive ontologies. These ontologies are then explored by association rules aiming to link semantic descriptor (a concept) to a set of visual features. The obtained feature collections are selected according to the annotated query images. Different strategies have been experimented and their results have shown an improvement of the retrieval task based on relevant feature selections.

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1 INTRODUCTION

The development of efficient image retrieval approaches is a very active research area. Content based image retrieval approaches (CBIR) are particularly very popular because they are automatic and do not rely on the users to perform the retrieval process (Liu et al., 2007). Instead, they use internal description consisting of visual feature vectors to index images. Visual feature vectors that index the image database are numeric information extracted from image pixels using image processing and analysis techniques. In literature the problem of image indexation has been addressed using two different visual feature categories which are common visual features and field specific visual features (Mussarat et al., 2013).

Common visual features (low-level) can be color, texture or shape features. They can be extracted from a whole image (global approach) or from specific regions (local approach) using clustering techniques (Lavenier, 2001).

Field specific features are generally motivated by a particular application context. For instance, to address the face recognition problem, the Viola and Jones detection framework has been proposed (Viola and Jones, 2004). The work introduced in (Sarfraz and Hellwich, 2008) propose a robust procedure for face recognition based on a feature taking into account facial appearance shape and illumination.

Several low-level and domain specific features have been proposed in the literature. However, the accuracy of retrieval results remain far from users expectations (Smeulders et al., 2000). On one hand, the adoption of sophisticated features can improve results, but highlights the high algorithms' complexity, the computation time and the feature vectors' dimension problems (Vinukonda, 2011). On the other hand, applying a large number of features disperses the retrieval focus and makes the process time consuming.

Our idea is to integrate a feature selection mechanism in the image retrieval process, aiming to guide the selection of features to be used to index query images. The proposed selection allows retrieving images based on suitable features to the current query image instead of applying random sets of visual features. Our contribution consists in building feature collections in line with specific semantic content, and providing a dynamic selection mechanism of visual feature sets. The selection mechanism that we propose is based on the user query annotation which is considered by our approach as a relevant source of semantic content description.

The remainder of this paper is organized in 3 sections. In section 2, we review some common CBIR implementations. After discussing the study of related works, we detail our approach in section 3. The implementations of the proposed approach as well as the experimental results are introduced in section 4. Finally, discussion and results analysis as well as future works are presented in conclusion.

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2 OVERVIEW AND MOTIVATIONS

In this section we present some related (but not exhaustive) works on image retrieval approaches using low-level visual features. Then, we discuss the classical approaches problems and propose our motivations to dynamic feature selection giving a query image.

2.1 Visual Features for CBIR Approaches

Several low-level visual features, related to color, texture and shape; have been proposed in literature and widely used in retrieval approaches. We review here some common CBIR approaches.

The existing implementations of CBIR approaches are mainly based on different feature categories. The first CBIR systems rely on one feature. Since color is an intuitive image content descriptor and simple to extract. It was used as a basis for several implementations.

In (Pass et al., 1996), an approach based on histogram with a spatial dimension has been proposed. The experiments have been done on a large diversified image database and have shown the improvement of the retrieval results compared to histogram based approaches. This approach and several other approaches rely on color histogram or some variations of it. However, these approaches store the extracted information for each image which may require significant space. Thus in (Paschos et al., 2003), an approach based on the chromaticity diagram has been proposed. This approach reduces the required space and maintains the effectiveness of the results compared to classical approaches.

Color is a restrictive parameter especially when dealing with specific fields such as face detection or footprint recognition. In this fields, the detection of exact shapes seems to be necessary. Thus, another class of approaches based on shape features has been proposed. CBIR systems have been used for a diverse range of images, however, shape detection algorithms have usually been designed for special issues. We focus here on works that implement shape features for image retrieval purpose.

In (Lin et al., 2004), an efficient and robust shape-based image retrieval system is proposed. The Prompt edge detection method is used to detect edge points. Then the low-to-high sequence (LHS) shape representation method is introduced. The results proved the method robustness and effectiveness. But it is worth noting that shape based approaches have higher complexity. In (Hejazi and Ho, 2007), an image retrieval approach based on classical texture features, such as orientation, directionality, and regularity has been proposed. Their discriminant power has been compared to the MPEG-7 texture feature through experimentation on aerial images.

Other CBIR systems combining different categories of features have been proposed. In (Jalab, 2011), a color layout and Gabor texture descriptor based approach has been proposed. The Color Layout Descriptor (CLD) represents the spatial distribution of colors in an image. However, Gabor texture feature describes the texture distribution of similar colors in an image. The integration of the two features has significantly improved the retrieval performance. Retrieval results were compared with two other approaches ((Hiremath and Pujari, 2007) and (Hafiane and Zavidovique, 2008)) and proved to be more accurate.

The approaches presented above are entirely based on visual aspects. In fact, they focus mainly on the problem of designing new features and finding possible combinations between existing features. These proposals do not take into account the users perception usually expressed in textual annotations. However, despite the large amount of approaches such as machine learning, relevance feedback and ontologies, the research area is still open and new approaches appear every day. These approaches are promising, but the use of visual features can be inconsistent in some context with semantic descriptors. The correlation of joint features that should be applied is always given in order to reduce computation time of retrieval processes, analyze feature performance or to fit data set specificity.

Unfortunately, despite this large number of implementations, several problems persist, mainly how to select an initial set of suitable features for a specific semantic content. In literature, the main approaches randomly establish a number of visual features to be applied during retrieval (Deselaers et al., 2008), ignoring in someway specific semantic information related to the query image and that could be beneficial in establishing a coherent understanding of the real human perception.

2.2 Motivations

In the context of image indexing for retrieval purposes, it can clearly be seen that content based approaches, using different features and applied on the same image dataset, perform differently (Jalab, 2011). As a result, the research quality heavily depends on the selected features.

In addition, image retrieval systems usually establish previously a given set of visual features which are used for any application domain. Thus, for two queries, it is possible to obtain completely different precision values (a high precision of retrieval results for one and a low value for the other), although the retrieval process relies on the same features. In this case, semantic information deduced from image annotation is ignored and retrieval is performed statically without taking into account the image specific semantic content.

Furthermore, the selection of a set of visual features for a query image that is guided by its semantic content can be considered as an interesting idea.

Our purpose is first to provide a set of relevant visual features for each query image, given its semantic content. This enables to improved retrieval results accuracy, to substantially reduce the feature vectors number and to decrease the processing time. So, the aims of this paper can be summarized in:

- Building visual features collection according to semantic content. These collections allow associating, for a concept, a set of suitable visual features that should be applied on queries containing this concept. Suitability is deduced from the different application domains reviewed in literature works.
- Integrating relevant visual feature selection during the retrieval phase thus allowing a dynamic retrieval process based on query image semantic content. The feature selection uses image annotation to select visual feature collection and then extract the most relevant features.

3 RELEVANT VISUAL FEATURES' SELECTION FOR IMAGE RETRIEVAL

The proposed approach is part of a research line with wider scope, in which a hybrid retrieval approach has been defined (Allani et al., 2014). Our idea is to use both visual features and textual content in order to perform a pattern-based retrieval. Our work has focused on structuring image dataset into a set of patterns which are semantically and visually rich. Then we retrieve results using similarity measure computed between query similarity and the patterns.

Let's consider a query image composed of the "sky", two "divers", "ocean", "sand beach" and the "clouds". This image represents different objects and so can be described using different visual features. Whereas the "sky", the "ocean" and the "sand beach" are characterized by their uniform texture, the "diver" and the "clouds" are characterized by their specific shape (shape of a person, shape of the clouds). Moreover, the image represents many meta-data characteristics. We aim here to apply, during retrieval of similar images, features suitable to the semantic content and the meta-data of the image.

Shape features can be used to index images representing shapes, same for texture. Also, meta-data characteristics can be used to select appropriate visual features. For example a high resolution involves a time consuming processing for feature extraction, so features with high complexity (for example region based shape features) should not be applied with such images. As a result, for this specific image, using texture and shape features such as Edge Histogram and canny edge detector which is a contour based shape feature, can provide more relevant retrieval results because they are suitable to the query image.

The overall architecture of our approach is illustrated in Figure 1. The process begins with building a set of visual features' collections dedicated to specific concepts or meta-data characteristics. Building process is performed given a set of annotated images and a set of suitability rules deduced form literature. Image dataset can be updated when new images are added to it.

As depicted in Figure 1, our retrieval process, based on relevant feature selection, is performed in two phases: online and offline phases. In the next paragraph the different steps of our retrieval approach will be detailed.

The first step is to specify the set of candidate visual features on which selection mechanism will be performed. Visual feature vectors are computed on the image dataset and stored (cf. Figure 1 Step (1)). They are then clustered into regions (cf. Figure 1 Step (3)).

Concepts are then extracted from image annotations. A disambiguation step, based on WordNet [1], is performed in order to retrieve the good synset (sense) that corresponds to each word (cf. Figure 1 Step (2)). The set of concepts associated to all of the image dataset is stored. Finally, a unification step based on WordNet and aiming to get common super-concepts is performed. For example, two image annotations containing the words "Laguna Colorado" and "Green Lake" will be processed. The co-occurrences of the two words are substituted by their lowest common ancestor which is "lake".

The previously described steps allow getting a visually and semantically indexed image dataset. Next we define, given the semantic content of the dataset,

[1] http://wordnet.princeton.edu/

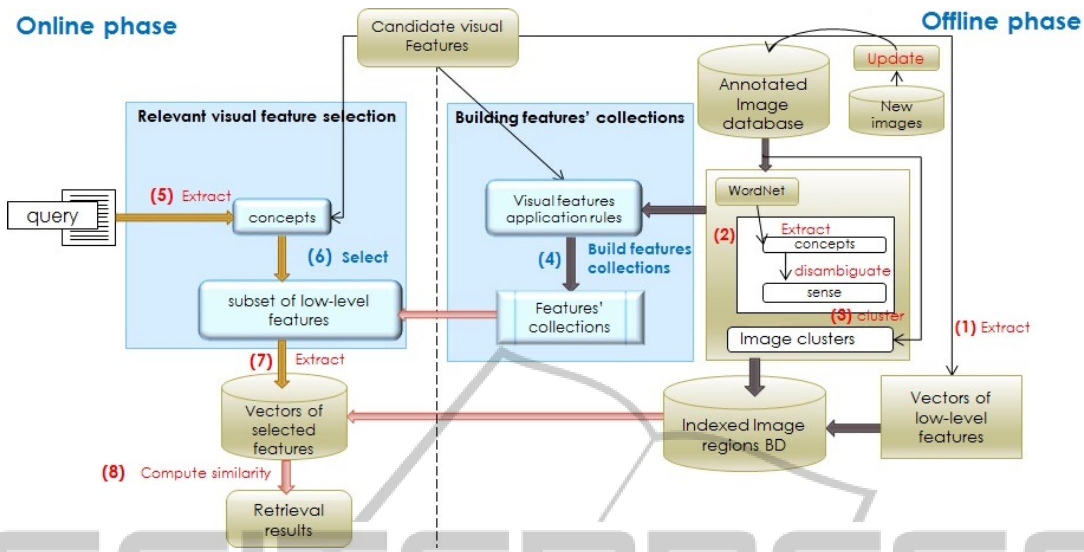

Figure 1: Relevant visual feature selection based approach.

the visual feature collection. Image semantic content (concepts) and meta-data are first associated to appropriate visual features. These associations known as Application rules (cf. section 3.2) define the relatedness between semantic content or meta-data and low-level visual features. They are deduced from the best practices or benchmarks collected from literature works on CBIR implementations. In order to build a valid set of rules, reflecting high correlation between semantic and visual aspects, we consider about 40 literature works covering several low-level visual features and different image datasets.

Thereafter, based on the concepts used to describe the image dataset, we propose a mechanism for building visual features' collections that are adapted to semantic content of query images. This approach analyses concept simultaneous presence frequencies to outline relevant visual features for a given query image. For each concept, related concepts (used with it in an image annotation) are collected and their presence frequencies for each image are analysed. Inconsistent concepts with frequencies lower than a threshold α are removed. In contrast consistent concepts are considered to build collections of visual features based on application rules (cf. Figure 1 Step (4)). These collections will be used next to select relevant visual feature collection suitable to query images.

During the online phase, a query image annotated or not is introduced. If the query image annotated, then concepts are extracted from annotation and disambiguation is performed (cf. Figure 1 Step (5)). When visual feature collection are selected for all the concepts, the number of visual features can be high. Thus, a reasoning mechanism should be applied to keep the most relevant features (cf.Figure 1 Step (6)). Finally, a similarity measure is used to retrieve similar images (cf. Figure 1 Step (8)).

3.1 Visual Features, Meta-data and Image Content Ontologies

The proposed approach takes into account the semantic content and the meta-data characteristics of the query image file, to set up relevant low-level feature collection. In order to organize the various information, we need to formally represent knowledge within each of the cited domains.

Ontologies are powerful knowledge representation tools that provide an explicit specification of knowledge in a structured and organized manner. They allow enrichment and direct access to several types of relationships between the different concepts (Besbes and Baazaoui Zghal, 2014).
Thus, we propose to model three ontologies: image semantic content, meta-data and low-level features.

First we build a semantic hierarchy integrating concepts used to describe images textual content. Each image in the database should be represented by at least one concept of the image semantic content ontology.

Figure 2 illustrate the semantic content ontology which is a unified characterization of images semantic content. Each node of this hierarchy represents a concept and each edge represents the relationship "Is-a". An image can be described by a set of concepts and their relationships.

Definition 1 (Image Content Ontology)**.** *Let O_C be the image content ontology. The ontology concepts*

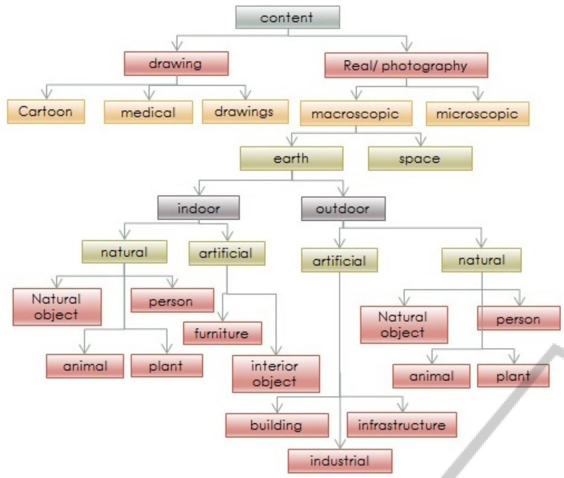

Figure 2: Image content ontology.

are noted:
$C = \{c_1, \cdots, c_k\}$ *is the set of concepts represented by the leaves of the ontology* O_C *.*

Non annotated images do not have rich semantic description, however, they rely on the surrounding textual information as meta-data. Meta-data provide useful information on images namely the image author, device, format, description, resolution etc.

We build a hierarchy to represent meta-data characteristics as well as the possible values of each characteristic. Image meta-data ontology is more or less sophisticated hierarchy established to provide a unified description for image characteristics in spite of characteristics values heterogeneous nature. In the proposed hierarchy, nodes represent image file characteristics and associated values, and edges represent the relationship ”Is-a”. Each image is represented with many characteristics values of the meta-data ontology.

Definition 2 (Meta-data Ontology)**.** *Let* O_M *be the image meta-data ontology.*
Image meta-data characteristics are noted:
$M = \{m_1, \cdots, m_v\}$.
A characteristic $m_i, i \in 1 \cdots v$, m_i *is associated to membership values.*
Let V_i *be the set of possible values associated to* m_i.
$V_i = \{v_{i1}, \cdots, v_{ik}\}$ *defined on* $(M \times D_{m_k \in M})$ *for* $k \in 1 \cdots v$

For example, an image has a ”high” resolution, a low size, ”nature scene” as a title and ”JPEG” extension.

Each characteristic of the image file could be represented by a set of values (depending on the characteristic domain). For example, if m_i represents the resolution, we associate to this characteristic the values ”low”, ”average” and ”high”.

In order to manage visual features studied in different literature works, we build an ontology for visual features (cf. Figure 3). This ontology has the advantage of being extendible (a new feature or a new use of an existing feature) and to provide an organized description taking into account possible relationships between features. Thus, features ontology is a unified characterization of low-level features. it is a hierarchy where the nodes represent features categories (shape, color, color), application mode(global, local) and application domains (specific, generic). Visual features from different categories and with different use are integrated in this hierarchy. The leaves represent visual features and the edges represent the relationship ”Is-a”.

Definition 3 (Visual Features Ontology)**.** *Let* O_F *be the visual features ontology.*
We note F *the set of available visual features:*
$F = \{f_1, \cdots, f_k\}$.

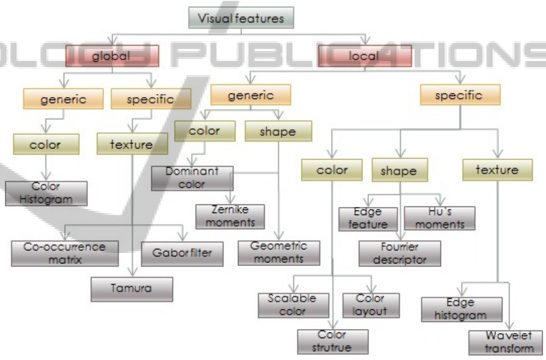

Figure 3: Visual features ontology.

3.2 Application Rules

The analysis of several literature works allowed us to identify several feature application domains. For instance, edge histogram is used in several works on natural image datasets and provides efficient retrieval results. Thus, we make use of this observation and extract an application rule assuming that edge histogram is associated to natural images. Following the above assumption, we build a set of application rules for a set of candidate visual features related to color, shape and texture.

We use the previously defined ontologie notations of the concepts in rules reformulation. As a result, each application rule is expressed according to a concept from O_C or from O_M and a concept from O_F.

However, application rules correspond usually to general concepts such as nature, object or texture. However, concepts in query image annotation are very specific. Thus, using the image content ontology

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as well as WordNet allows deducing implicit application rules. For example, *Building → Color-Layout* is a rule deduced from literature works. A query image with a ”hospital” or a ”farm house”, which are concepts related to building, will be associated to the feature Color Layout.

Definition 4 (Application Rules). *Let $I = \{I_1, \cdots, I_N\}$ is the set of images in the database where $N = \sharp I$ is the total number of images.*
We note R_i a feature application rule:
$R_i : \{d_l\}_{l \in 1 \cdots p} \rightarrow c_i$, where $1 \leq p \leq k$ and such that $\sharp\{d_l \in D\} \succ 0$.

3.3 Visual Feature Collections: Building and Selection

As presented above, our goal is to find out relevant features given the semantic content and to decide which feature collection should to be applied together. To deal with the second problem, we introduce the collections of features idea. A collection of features is a set of low-level features suitable to a specific concept or characteristic. In order to create the feature collection, we adopt an inductive reasoning (Akdag et al., 2000) in which the premises seek to supply evidence. In our case, the premises are the concepts used in annotation. As previously precised, concepts used to annotate the image dataset are unified and stored. For each image a final set of concepts is identified. For each concept, we extract images where this concept has been used. Then, we compute appearance frequencies of other concepts in these images. This allows to deduce which concepts are frequently used with the concerned concept.

Definition 5 (Feature Collection Building). *Let w_i be the final set of concepts associated to the image I_i.*
$w_i = \{c_{i1} \cdots c_{ik}\}$ are the concepts in w_i
For the concept c_h let I_h be the set of images where c_h exists. m is the cardinality of I_h
For the set I_h, $w_h = \{c_{l1} \cdots c_{lp}\}$ are the concepts simultaneously used with c_h
We compute $f_{l1} \cdots f_{lp}$ which are the numbers of occurrences of $c_{l1} \cdots c_{lp}$ simultaneously with c_h from the images in I_h devided by m.
Concepts c_k with $f_k \geq \alpha$ are retained.

We also apply treatments on image meta-data in order to obtain a unified description of meta-data. Finally, on the whole image collection we compute, for every specific concept, other concepts presence frequencies in order to deduce the possible feature collections. The obtained set of concepts associated to the concerned concept allows to deduce the feature collection. A relationship between the concepts and the image content ontology is deduced based on WordNet relationships. Then, using these relationships we deduce for each concept an application rule. As a result we obtain a set of features that we associate to the concerned concept. It is worth noting that each collection is characterized by a priority factor consisting of the ratio of the images where the concerned concept appeared and the total number of images in the database. Moreover, image dataset update leads necessarily to changing in the concepts. In this case, collections update is also needed.

When a query image is introduced, image annotation is processed in order to extract concepts and use them to select relevant features to apply during the retrieval process. To each concept, a collection of features is proposed. In order to get the final features collection, a reasoning step taking into account priority of the different collections is performed. Finally, given the selected features, query image is indexed and similarity is computed (cf. Figure 4).

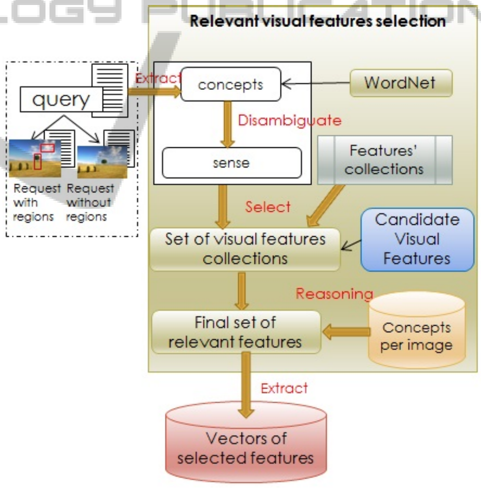

Figure 4: Visual feature selection for image retrieval.

4 EXPERIMENTATION AND RESULTS ANALYSIS

Our proposal has been implemented and evaluated in order to show its interest in image retrieval. From more technical point of view, the frameworks that have been employed are Java as programming language. The source codes of visual features implementations are provided by the jFeatureLib[2] and the LIRe[3] libraries.

[2]https://code.google.com/p/jfeaturelib/
[3]https://code.google.com/p/lire/

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Different strategies have been defined to allow the evaluation of the improvement degree provided by our approach. Query images are classified given their content into 6 classes. On each class of query images we perform 7 retrieval strategies given the feature(s) categories. The goal is to get the higher precision and recall values for a strategy conform to an image class. For instance, the best value of precision and recall obtained for textural images correspond to texture based retrieval.

To evaluate our approach, we used the Image Clef 2013 dataset[4]. There are 117 query images (with the qrels file) in different sizes (average image dimensions: 480*360 pixels) and representing various objects and themes.

4.1 Experimental Setup

For measuring the image retrieval effectiveness we used as evaluation metrics:

- The exact precision measure (P@10)
- The recall measure

For the experiments we apply the 7 following retrieval strategies: SBIR (shape strategy with canny edge detector); TBIR (texture strategy with edge histogram and the Gabor filter); CBIR (color strategy with color layout and scalable color descriptors); TSBIR (texture and shape strategy with edge histogram and canny edge detector); CSBIR (color and shape strategy with color layout and canny edge); CTBIR (color and texture strategy with color layout and edge histogram); SCTBIR (shape, color and texture strategy with canny edge detector, color layout and edge histogram). These strategies are applied each time on the following 6 classes of query images in order to evaluate the impact of our feature selection approach given the image semantic content: S-Class (images with object shapes) ; T-Class (images with textures); TS-Class (textural and shape images); CS-Class(color and shape images); CT-Class (color and textural images); TSC-Class (texture shape and color combined images).

4.2 Evaluation Results

Figure 5 shows the results in term of precision for the top 10 retrieved images according to the proposed strategies. The obtained precision result for the strategy texture based image retrieval (TBIR) is clearly higher than other strategies when applied on texture images class (CT). The same observation could be

[4]http://imageclef.org/SIAPRdata

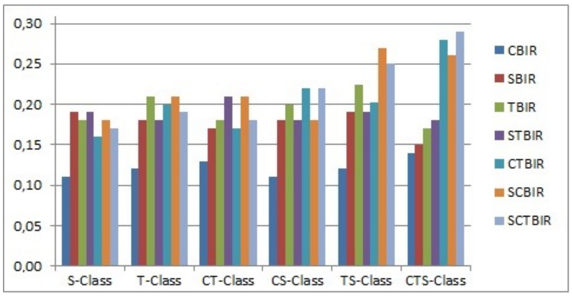

Figure 5: Precision.

noted when the strategy applied is associated to the image class.

Figure 6 shows the results in term of recall. The recall values are higher for the shape and texture based image retrieval (STBIR) strategy when applied on the shape and texture class. This allows to deduce the impact of relevant feature selection on the retrieval.

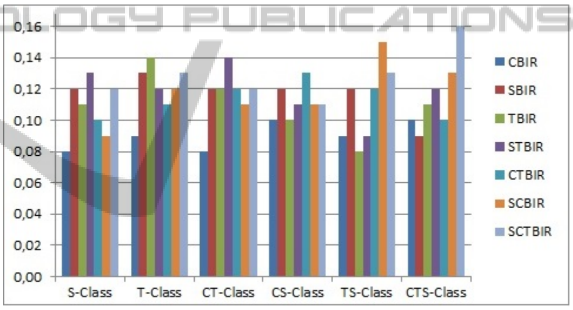

Figure 6: Recall.

To complete these results, we computed the improvements for image class of the adapted strategy in front of the average precision and recall values of the other strategies.

Figure 7 and figure 8illustrate retrieval results using the CTBIR strategy and the SCTBIR strategy.

5 CONCLUSION

In this paper, an image retrieval approach has been defined. It relies on feature set collections building and relevant feature selection mechanisms. These mechanisms allow a dynamic low-level feature selection guided by the query image semantic content. In this work, we have conducted an elementary experimental study where we are focused on the improvement given by our approach. It is worth to be noted that the preliminary results obtained with a targeted selected features are more relevant than those obtained

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Figure 7: Retrieval results using CTBIR strategy.

Figure 8: Retrieval results using SCTBIR strategy.

with features selected randomly. An advanced implementation and experiments are in progress to evaluate the proposed approach: ontologies, rules and feature building.

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