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METHODS FOR KNOWLEDGE DISCOVERY IN IMAGES

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Abstract. In this paper we describe an automated method for generating images annotations, taking into account their visual features. The semantic rules map the combinations of visual characteristics (colour, texture, shape, position, etc.) with semantic concepts, capture the meaning and understanding of a domain by an expert, namely, which visual primitives are definitive for the semantic concepts of an image category. These rules are represented in Prolog and can be shared and modified depending on the updates in the respective domain.

Keywords: semantic image annotation, visual characteristics, association rules, image mining, Apriori algorithm.

1. Introduction

A lot of researches were developed to investigate automated techniques for extracting low-level audio/ video features that together generate semantic descriptions for multimedia content. Because of visual data quantity and complexity, their annotation is a big time consumer, expensive and very subjective. Even if in the last two decades a big number of techniques were developed, the generation of image semantic annotation remains a significant challenge.

Methods based on machine learning are used in [1, 3, 13, 15], and manually annotate the training set of data for generating graphs, statistical models or other indexing techniques for big data collections.

A method that integrates the ontology within a method based on machine learning techniques for image annotations is proposed in [9]. The utilization of machine learning techniques for eliminating the semantic gap provides powerful methods for discovery of complex and hidden relationships or mappings.

The relationships between low-level features and semantic descriptions are hidden and they can't be manipulated or examined by a domain expert. So, detailed and specific tests can be effectuated for ensuring the performance.

Ontology for multimedia data was developed in [4, 13]. These methods use relationships described in ontology or thesaurus for permitting complex semantic queries on annotated multimedia collections or for inferring new information.

So, in the last decades, ambitious tentative to train machines to learn, index and annotate images were developed with great progress [7, 8]. The power of association rules is used in different domain, from semantic web to image mining.

The rules were used for discovering knowledge in [2, 11]. If they are defined in a transparent way, the rules are capable to clarify the undestanding of a domain paradigm.

In general, the semantic gap is due to the following problems:

- The difficulty of the complete extraction of the semantic concepts from images, necessitating the objects recognition and understanding, known as the problem of semantic concepts extraction [7].
- The complexity, ambiguity and subjectivity of human interpretation, known as the problem of semantic concepts interpretation [7].

The problem of semantic concepts interpretation is due to a lot of factors, like the cultural differences, education, which affects the user interpretation model [8]. Also, the human perception and judgment are not time invariant.

This study is started from the limitations regarding the researches in multimedia semantic modelling. This paper, proposes new approaches for image annotations, like: methods for generation of rules which identify image categories, a method for mapping low-level features to semantic indicators using the Prolog declarative language, the creation of a representation image vocabulary and syntax, and semantic image classification.

2. Image model

The model of knowledge representation constitutes the principal element of a retrieval system. An image *I* is logically modelled in two levels.

- At the low-level of the hierarchy, the image is represented as a set of visual low-level features *F{I}*. In our chosen representation, we have for each image a set of regions $R(I)=\{r_{ij}\}$ and the transition from the region set to the semantic concepts recognition represents the big challenge.
- At the higher- level image is represented by means of semantic indicators. Using a large set of experiments, a vocabulary is constructed to represent the semantic concepts of images. Also, a syntax, which captures the basic models from the human perception about images and semantic categories, is defined.

The selection of visual feature set and the image segmentation algorithm is the definitive stage for the semantic annotation process of images. From the realized experiments, we deduce the importance of the semantic concepts in establishing the similitude between images. Even if the semantic concepts are not directly related to the visual features (colour, texture, shape, position, dimension, etc.), these attributes capture the information about the semantic meaning.

2.1. Low-level features of images

2.1.1. The image segmentation after color feature

The ability and efficiency of the colour feature for characterizing the human perceptual similitude is strongly influenced by selection of colour space and quantization scheme. The HSV colour space quantized to 166 colours is used to represent the colour information [12]. Before the segmentation, the images are transformed from RGB to HSV colour space and quantized to 166 colours.

The transformation from RGB to HSV colour space is realized by means of a non-linear transformation. Then, the colour space HSV is quantized at 166 colours. The reasons for choosing the HSV colour space were: the colour space is complete, uniform, compact and natural. Because the hues represents the most important colour feature, it is necessary the most fine quantization. In the circle (Figure 1) that represents the colour, the primary colours, red, green and blue are separated by 120 degree. A circular quantization with a 20-degree step sufficiently separates the colours, such that the primary colours and yellow, magenta, cyan colours are each represented by three subdivisions. The saturation and the value are each quantized to three levels. This quantization produces 18 hues, 3 saturations, 3 values and 4 greys, so 166 distinct colours in the HSV colour space [12].

The extraction of colour regions and their characteristics is realized by the algorithm colour set back projection [12]. This algorithm detects the regions of a single colour. The process of region detection has four stages:

1. Transformation, quantization, filtering
2. Application of colour set back projection algorithm
3. Labelling of detected colour regions
4. Extraction of region characteristics.

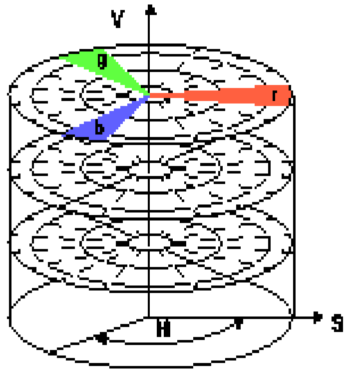

Figure 1. The HSV color space

A descriptor composed by colour, texture, dimension, spatial coherency, shape, position is associated to each colour region.

2.1.2. The region texture

In this paper, we use a method based on co-occurrence matrices. The co-occurrence matrix is based on repeated occurrence of configurations of pixels intensity in the image. These configurations vary with rapidity for thin texture and slower for roughly texture. In this method, the co-occurrence matrice is computed for each image region represented in the RGB colour space. In our case, a matrix was computed for each channel (red-R, green-G, and blue-B).

For an image $f(x, y)$, the co-occurrence matrix $hd_{\phi}(i, j)$ is defined such that, each entry (i, j) is equal to the number of times for that $f(x_1 y_1) = i$ and $f(x_2 y_2) = j$, where $(x_2 y_2) = (x_1 y_1) + (d\cos\phi, d\sin\phi)$ where d is the distance and ϕ the orientation between pixels [5].

This leads to 3 three quadratic matrices of dimension equal to the number of the colour levels presented in an image (256 in our case) for each distance d and orientation ϕ between pixels. The classification of texture is based on the characteristics extracted from the co-occurrence matrix [6]. The vector of texture characteristics extracted from the co-occurrence matrix is created using seven characteristics.

The *maximum probability* detects the most frequent motif.

The *energy* describes the uniformity of the texture. In a homogeneous image, there are very few dominant gray-tone transitions; hence the co-occurrence matrix of this image will have fewer entries of large magnitude. So, the energy of an image is high when the image is homogeneous.

The *entropy* measures the randomness of the elements in the matrix; when all elements of the matrix are maximally random, entropy has its highest value.

So, a homogeneous image has lower entropy than an inhomogeneous image. In fact, when energy gets higher, entropy should get lower.

Another image characteristic is the *contrast*.

Cluster shade and cluster prominence are measures of the skewness of the matrix, in other words the lack of symmetry. When cluster shade and cluster prominence are high, the image is not symmetric. In addition, when cluster prominence is low, there is a peak in the co-occurrence matrix around the mean values. For the image, this means that there is little variation in gray-scales.

Correlation measures the correlation between the elements of the matrix. When correlation is high, the image will be more complex than when correlation is low.

Three vectors of texture characteristics corresponding to each matrix, are computed considering the distance d=1 and orientation ϕ=0.

$$t_r = (t_{r1},...,t_{r7}), t_g = (t_{g1},...,t_{g7}),\\ t_b = (t_{b1},...,t_{b7}) \quad (1)$$

A single vector of texture characteristics is computed by combining the vectors values from equation 1:

$$t = \sum_{i=1}^{7} \sqrt{t_{ri}^{\ 2} + t_{gi}^{\ 2} + t_{bi}^{\ 2}} . \quad (2)$$

2.1.3. The region shape

Shape is an important characteristic of an object. The goal of shape descriptors is to uniquely characterize the object shape. Two shape descriptors are used in our experiments [16]:

- Eccentricity is the length ratio between the major and minor axes of the objects, smaller for rounded shapes and greater for distorting ones.
- Compactness is the ratio between the length of object's boundary and the object's area.

2.1.4. The spatial information

The spatial information of the region is also considered in the annotation of images. It provides the necessary information in the process of region indexing and semantic definition, like upper left, upper right, center, etc. The spatial information of each region is represented by two parameters, as in Figure 2: the centroid of the region *Cx,y=(Xc, Yc)* and the minimum bounding rectangle *(l,r,t,b)*, where *(l,r)* represents the coordinates of the upper left corner and (*t,b*) represents the coordinates of the bottom right corner.

2.1.5 The region indexing

A region is described in conformity with defined characteristics:

- The colour characteristic is represented in the HSV colour space quantized at 166 colours. A region is represented by a colour index which is, in fact, an integer number between 0..165. It is denoted as descriptor F1.
- The spatial coherency represents the region descriptor, which measures the spatial compactness of the pixels of the same colour. It represents the spatial homogeneity of a region in an image and is computed for identifying the 8-connected pixels of the same colour in a region. It is denoted as descriptor F2.
- A seven-dimension vector (maximum probability, energy, entropy, contrast, cluster shade, cluster prominence, correlation) represents the texture characteristic. It is denoted as descriptor F3.
- The region dimension descriptor represents the number of pixels from region. It is denoted as descriptor F4.
- The spatial information is represented by the centroid coordinates of the region and by minimum bounding rectangle. It is denoted as descriptor F5.
- A two-dimensional vector (eccentricity and compactness) represents the shape feature. It is denoted as descriptor F6.

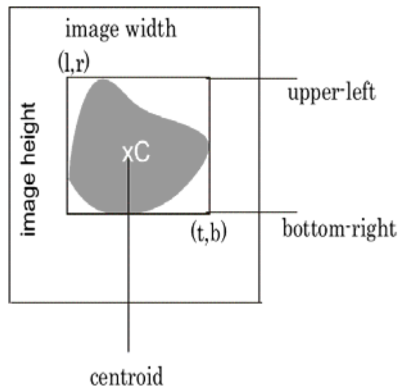

Figure 2. The representation of spatial information of image region

2.2 High-level features of images

In this study, the representation language is simple, because the syntax and vocabulary are elementary. The language words are limited to the name of semantic indicators. Being visual elements, the semantic indicators are by example the colour (colour-light-red), spatial coherency (spatial coherency-small, spatial coherency-medium, spatial coherency-big), texture (energy-small, energy-medium, energy-big, etc.), dimension (dimension-small, dimension-medium, dimension-big, etc.), position (vertical-upper, vertical-center, vertical-bottom, horizontal-upper, etc.), shape (eccentricity-small, compacteness-small, etc.).

The syntax is represented by the model, which describes the images in terms of semantic indicators values. The values of each semantic descriptor are mapped to a value domain, which corresponds to the mathematical descriptor.

The values domains for visual characteristics were manually experimented on images of *WxH* dimension.

A value of colour semantic indicator is associated to each region colour in the HSV colour space quantized at 166 colours. The colour correspondence between the mathematical and semantic indicator values is determined by experiments effectuated on a training image database. The colour correspondence is illustrated by the following examples:

- light-red (108), medium-red (122), dark-red (139);
- light-yellow (109), medium-yellow (125), dark-yellow (141);
- light-green (112), medium-green (130), dark-green (142);
- light-blue (116), medium-blue (136), dark-blue (148).

A hierarchy of values, which are mapped to semantic indicator values, is also determined for texture: texture-energy-big, texture-energy-medium, texture-energy-small, texture-entropy-big, texture-entropy-small, texture-entropy-medium, etc.

The correspondence of the entropy component of the texture is illustrated by the following examples:

- If $0 \le entropy \le 1$, then the region has entropy-small.
- If $1 < entropy \le 1.67$, then the region has entropy-medium.

A hierarchy of values, which are mapped to semantic indicator values, is also determined for shape, as in Figure 3 and 4: eccentricity-big, eccentricity-medium, eccentricity-small, and compactness-small, compactness-medium, compactness-big.

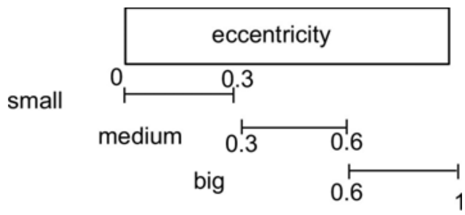

Figure 3. Correspondence between mathematical values of the visual shape feature (eccentricity) and semantic indicators

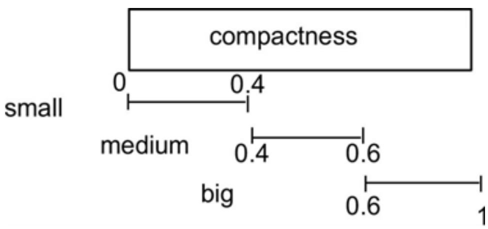

Figure 4. Correspondence between mathematical values of the visual shape feature (compactness) and semantic indicators

The mapping is similar for the other visual characteristics (dimension, spatial coherency, and position).

A figure is represented in Prolog by means of terms of the form *figure(ListofRegions)*, where *ListofRegions* is a list of image regions.

The term *region(ListofDescriptors)* is used for a region representation, where the argument is a list of terms used to specify the descriptors (semantic indicators), and for semantic indicators the term is of form:

```
descriptor(DescriptorName,
           DescriptorValue).
```

The mapping between the values of the low-level (mathematical) descriptors and the values of semantic indicators is based on experiments effectuated on images from different categories. We use facts of the form:

```
mappingDescriptor(Name,
     SemanticValue,ListValues).
```

Name is the name of the semantic indicator, *SemanticValue* is the value of the semantic indicator (descriptor), *ListValue* represents a list of mathematical values and closed intervals, described by the following terms: *interval(InferiorLimit, SuperiorLimit)*. For example, consider the facts:

```
mappingDescriptor(colour,  red_medium,
    [144, 134]).
mappingDescriptor(colour,red_dark,
    [100,interval(105, 111), 123]).
```

The semantic indicator red_medium has the values 144 and 134, and red_dark has the values 100, 123 and all the values from the interval [105, 111].

The mapping mechanism has the following Prolog representation:

```
mapDescriptor(descriptor(Name,
MathematicalValues),descriptor(Name,
SemanticValue)):-
   mappingDescriptor(Name,
   SemanticValue, ListValues),
   containValue(ListValue,
   MathematicalValue).

containValue([Value|_], Value).

containValue([interval(InferiorLimit,
    SuperiorLimit)|_], Value):-
    InferiorLimit=<Value,
    Value=< SuperiorLimit.

containValue([_|ListValues], Value):-
      containValue(ListValues,
Value).
```

3. Knowledge discovery in images

The knowledge discovery in databases, an important part of data mining, is defined as the automated discovery of usefull, unknown, non-trivial information [4].

The main component in image discovery is the identification of similar objects from images.

The association rules discover the information about the elements that are frequent. The formal representation of an association rule is the following. Being given $I=\{i_1, i_2, ..., i_m\}$ a set of distinct elements, D is called a transaction set, where each transaction T is a subset of I or $T \subseteq I$. A transaction T contains X if and only if $X \subseteq T$. An association rule is an implication $A=>B$, where $A \subseteq T$, $B \subseteq T$, $A \cap B = \emptyset$. A and B are called the body, and respectively the head of the rule. The support of a rule is defined as the percent of transactions in which both the body (A) and head (B) of the rule are present. If a rule $A=>B$ has support $\%s$, it means that $\%s$ of transactions from D contain $A \cup B$. The confidence is defined as the ratio between the number of transactions in which both the body (A) and head (B) of the rule are present, and the number of rules in which only the body is present [14].

If the rule $A=>B$ has the confidence $\%c$, it means that $\%c$ transactions from D contain $A \cap B$.

The support estimates the probability $P(A \cup B)$, and the confidence estimates the conditional probability $P(B|A)$.

In image discovery, to label each object, which appears in an image, is a complex task.

In this paper, the knowledge mining from images is used for the definition of rules, which convert the low-level primitives of images into semantic high-level concepts. The methods used in this study bring important improvements related to the detailed descriptions of images, which are necessary for defining relationships between:

- objects/regions,
- classes of visual characteristics,
- objects/regions and classes of visual characteristics.

4. Semantic rules generation for images

The image database DB is used in the learning phase, and contains n image-examples, labelled by a semantic concept, for which we train the system and generate semantic rules. In the learning phase, the aim is to automatically generate semantic rules R based on labelled image-examples, which indentify the semantic concepts of images. A rule determines which is the set of semantic indicators, which identify the best a semantic concept. In the testing/annotation phase, the generated semantic rules are used to label each image of the testing subset, namely the images from DB, but that are not in U, with one or more concepts.

A semantic rule is of the form:

semantic indicators -> semantic concepts

The stages of the learning process are:

- relevant images for a semantic concept are used for learning it.
- each image is automatically processed and segmented, resulting the primitive visual features computed as it is described in section 2.
- for each image the primitive visual features are mapped to semantic indicators as it is described in section 2.
- the rule generation algoritmh is applied to produce rules for identifying each semantic category from the database.

A Prolog mechanism for rules inference is used to recognize the semantic high-level concepts because the images and rules are represented in Prolog.

In our system, the learning of semantic rules is continuously made, because when a labelled image is added in the learning database, the system continues the process of rules generation.

4.1. The description of the algorithm for rules generation

The algorithm for semantic rules generation is based on A-priori algorithm of finding the frequent itemsets.

The choice of the itemsets and transactions is a domain dependent problem. In the case of market analysis, the itemsets are products, and the transactions are itemsets brought together.

The aim of mining image association rules is to discover semantic relationships between image objects. For using association rules that discover the semantic information from images, the modeling of images in the terms of itemsets and transactions is necessary:

- the image set with the same category represents the transactions,
- the itemsets are the colours of image regions,
- the frequent itemsets represent the itemsets (colours of image regions) with support bigger or equal than the minimum support. A subset of frequent itemsets is also frequent,
- the itemsets of cardinality between 1 and k are iteratively found,
- the frequent itemsets are used for rule generation.

In our method, the Apriori algorithm is used for discovering the semantic association rules between primitive characteristics extracted from images and images categories/semantic concepts.

We have the following contraint: the semantic association rules have the body composed by conjunctions of semantic indicators, while the head is the category/semantic concept. A semantic rule describes the frequent characteristics for each category, based on the Apriori rule generation algorithm. The algorithm of semantic rule generation is described in pseudo-code:

```
Algorithm: the rule generation for each
image category in the database.
```

```
Input: the image set:each image
 I = ( f1, …,fk), where fm is the colour
 of the image region m.
Output: the set of semantic association
        Rules.
Method:
       Ck: the colour set of k-length
       Lk: the frequent colour set of
        k- length
       Rules: set of rules contructed
       from frequent itemsets for k>1
       L1= {frequent colors}
       for(k=1; Lk!=null; k++) do begin
          Ck+1=generated candidates from
       Lk;
       for each transaction t in database
           do begin
                  *increment the number
          of itemsets which appear in
          t  Lk+1= itemsets from Ck+1
             that have the support
             greater and equal with
             suport_min
           end.
       end.
       Rules=Rules + {Lk+1->category}.
```

4.2. Rules elimination

The number of rules that could be generated is usually great. In this case two problems exist: the first one is that the set of rules can contain noises information and affect the classification time. Another problem is the big number of rules that can also affect the classification time. This is an important problem in the applications, which necessitate rapid response. On the other side, the elimination of rules can affect the classification accuracy. The used elimination methods are the following: elimination of specific rules and keeping of the ones with big confidence, and the elimination of rules that can introduce errors in the classification process.

The following definitions introduce some notions used in this section.

Definition 1: Given two rules R_1->C and R_2->C, the first rule is called general if $R_1 \subseteq R_2$. The second one is specific.

Definition 2: Given two rules R_1 and R_2, R_1 is stronger than R_2 (or R_2 is weaker than R_1):

(1) If R_1 has confidence greater than R_2,

(2) If the confidences are equal, but the support(R_1) is greater than support(R_2),

(3) If support(R_1) = support(R_2) and confidence(R_1) = confidence(R_2), but R_1 has fewer attributes than R_2.

The elimination algorithm of weak and specific semantic rules is described in pseudo-code:

```
Algorithm. Elimination of weak and
specific rules.
Input: set of semantic rules, S,
discovered for each category, C.
Output: a set of rules which will be
used for classification.
Method:
      *Sort the rules for C category in
       conformity to Definition 1
       foreach rule in S do begin
           *Find the rules most specific
           *Eliminate the rules with
     smallest confidence
       end.
```

5. Semantic image classification

The set of semantic rules represent the classifier. It is used to predict which category has to be assigned to an image from the test database. The classification process matches each rule with a given image. The matched rule with the best confidence is chosen to identify the image.

Before the classification, the image is automatically processed:

- the mathematical and semantic descriptors are generated; the semantic descriptors are saved as Prolog facts,
- the semantic rules are applied to the facts set, using the Prolog inference engine.

In this study, a new method called the “perfect match classification method” for semantic annotation /classification of images, using semantic rules is proposed and developed.

A semantic rule matches an image if all the characteristics, which appear in the body of the rule also appear in the image characteristics.

```
Algorithm. Perfect match classification
algorithm.
Input: new image I which has to be
classified and the rules set Rules, each
rule having the confidence Ri.conf.
Output: the image category which the
image will be annotated with, and the
score of matching.
Method:
     S = null
  Foreach rule R in Rules do begin
     If  R matches I then
     *Keep R and add R in S
      I.score = R.conf
        *Divide S into subsets based
           on identified category:S1,…,Sn
         foreach subset Sk from S do
           *Add the confidences of
            all rules from Sk
                   *Add I image in the
            category identified by
            the rules from Sk with
            the greatest confidence
                   I.scor = max∑Sk
               end.
             end.
         end.
```

6. Experiments and results

The application of the learning results – semantic rules, on other images than the ones used in the learning process is much more difficult. In the experiments realized through this study, two databases are used for learning testing process.

The database used for learning contains 200 images from different nature categories and is used to learn the correlations between images and semantic concepts. All images from the database have JPEG format and are of different dimensions. The database used in the learning process is categorized into 50 semantic concepts. The system learns each concept by submitting approximatively 20 images per category. Even if the annotation system is based on learning, this can be used for images from different domains. Some examples of the images category from the learning database are illustrated in Figure 5.

Figure 5. Examples of image categories from the learning database

It is considered that an image was correctly classified by the system, if the category predicted by the computer is correct.

The performance metrics, recall and precision, are computed to evaluate the efficiency and accuracy of the rules generation and annotation methods.

These parameters are defined by the following equations:

$$precision = \frac{No.\ of\ relevant\ \ images\ \ retrieved}{No.\ of\ total\ \ images\ \ retrieved} \quad (3)$$

$$recall = \frac{No.\ of\ relevant\ \ images\ \ retrieved}{No.\ of\ total\ relevant\ \ image\ \ in\ the\ database} \quad (4)$$

Experiment 1 *– The evaluation of the classification process for images from Cliff category*

- Five semantic rules were generated to identify the "cliff" category.
- The test database contains 25 relevant images for "cliff" category.
- The semantic rules for "cliff" category are applied to all images from the test database.
- In the first 10 images, classified by the increase score, it is verified which is correctly classified (C) or wrongly classified (W).
- The result is: C, W, C, C, W, C, C, C, C, W.
- In the following table, the values of the recall and precision are computed based on equations 3 and 4:

Tabel 1. The values of the recall and precision parameters

Image Rank	Recall	Precision
1.	1/25	1/1
2.	1/25	1/2
3.	2/25	2/3
4.	3/25	3/4
5.	3/25	3/5
6.	4/25	4/6
7.	5/25	5/7
8.	6/25	6/8
9.	7/25	7/9
10.	7/25	7/10

Experiment 2 *– For each category from the database, the percent of images correctly classified by the system is computed as in Figure 6.*

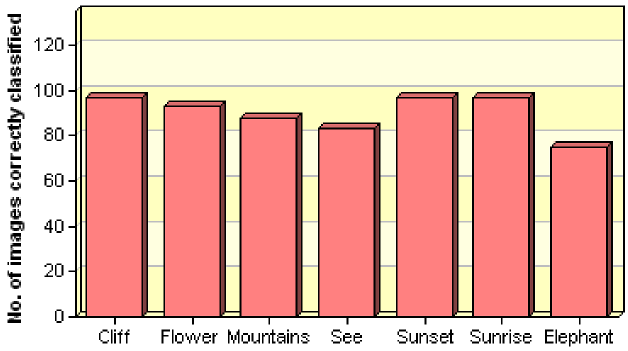

Figure 6. Category vs percent of images correctly classified by the system

7. Conclusion

In this study we propose a technique for semantic image annotation based on visual content. For establishing correlations with semantic categories, we experimented and selected some low-level visual characteristics of images. So, each category is translated in visual computable characteristics and in terms of objects that have the great probability to appear in an image category.

On the other hand, images are represented as a single colour regions list and they are mapped to semantic descriptors.

The annotation procedure starts with the semantic rules generation for each image category. The language used for rules representation is Prolog. The advantages of using Prolog are its flexibility and simplicity in representation of rules.

Our method has the limitation that it can't learn any semantic concept, due to the fact that the segmentation algorithm is not capable to segment images in real objects. Improvements can be brought using a segmentation method with greater semantic accuracy.

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