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An evaluation of perceptual classification led by cognitive models in traffic scenes

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Abstract

The objects extraction and recognition constitute the most important link in the image processing and understanding, and it cannot be achieved without a solid objects organization during the processing through the learning mechanisms. Most often, both the response time and the accuracy are undeniable criteria for applications in this field. Actually, a vision system needs to take into consideration these criteria, either in the structure, the methodology or the algorithmic aspect. Thus, we consider that the ontological study at the domain and task levels, in the vision systems, has become essential in order to provide a substantial assistance to the multitudes of applications in image processing. Concerning the domain knowledge, several patterns for structuring were proposed to improve the objects representation and organization, they often advocate the precision aspect on time and on the effort devoted to the recognition. In practical terms, clustering methods only focus on the accuracy aspect within a category, without considering the recognition aspect [1]. Thus, we propose in this study a new procedure of object categorization, which uses, according to the expertise in the domain, a fit evaluation that is able to adjust the level of partitioning. As a result, this procedure will find a compromise between the accuracy on the categories and the reduction of the supplied effort in recognition.

Keywords: Image processing, categorization, classification, recognition, vision.

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1 INTRODUCTION

At the decision making level and in all forms of interaction with the environment, categorization is considered as a cognitive process in the objects perception and understanding. A cognitive category is a set of objects considered as equivalent according to [2]. The categorization is applied to the psychological aspects and to the concept itself. It includes the establishment of classes or categories. The classification term can be considered as a synonym of categorization, and is applied principally to the processes and to the mathematical structures or techniques allowing the categorization. Thus, we consider classification as an organized and hierarchical system for object categorization. In many image processing applications, particularly in the road scenes (our experimentation field), we are confronted with the classification and recognition problem of different elements treated on various visual aspects: chromatic aspect (example: textures, colors), geometrical aspect (example: shape) and topological aspect (example: closeness).

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Most often, techniques of learning are used to solve this kind of problems, see [3]. We quote two main types of learning, depending on the information available towards data to classify: supervised learning and unsupervised learning.

In the supervised approach, every object is associated with a label which describes its class of membership, while in the unsupervised approach; the available data don't acquire any kind of labels or classes. It remains now to the system to extract a membership based on segmentation tasks, object extraction and object categorization. Many authors as [4], worked on the road scene interpretation, and their results encouraged the emergence of several projects, like: LAVIA3 [5], ARCOS [6] and PREVENT [7].

In most applications, the learning process establishes a relationship between individuals and predetermined classes (member or not) and not between the classes themselves. Indeed, in certain domains like road scenes (figure 1), objects are categorized separately. The process tends to offer solutions for special types of objects like vehicles, indicator panels or pedestrians, by treating them independently according to the classical theory of concepts. Thus, the "movement" can be detected for vehicles and pedestrians, but rarely considered as a shared property that permits to generalize dispositions for the whole "mobile" class. The cognitive categorization postulates a hierarchical organization on classes that extends object recognition when there is a lack of object features or imprecision. In some sense, we have to study the ontological aspect of knowledge in the domain. Then, the system can elaborate a learning method that satisfies the recognition time criteria by selecting the appropriate class in the hierarchy with minimum features and moving down (in the hierarchy) progressively with more features if precision is needed. Naturally, less categories leads a rapid recognition, but the reduction of categories introduces ambiguity on recognized members. Thus, the question is how to guide the categorization process to find a compromise between precision and time recognition.

This paper tries to answer, principally, to the above question. Our objective is to provide a tool evaluating the result of any category formation process with respect to precision and time recognition. In some way, the evaluation permits to construct a flexible structure able to be adapted according to the expertise in the application domain. We aim to develop a mechanism organizing the memory, which is designed to contain the known objects of the vision system, answering to the previous question. Obviously, this organization can be done by a hierarchy of abstractions which is often represented by a taxonomic tree under an ontological study. Each level in the tree is represented by a partition of objects, where the categories are formed on the basis of some common properties. Therefore, the choice of the level depends both on the expected precision (homogeneity of category members) and the response time. The presence of the tree can help to launch the image analysis and object matching in the same stage under a cooperative process (detecting a red color of game card can suggest to search diamond or heart shape). We suggested two measures; the first one concerned with homogeneity of each formed category in a partition and depends on a probability model. The second evaluates the effort of categorization process in term of time matching and depends on the size and the category representation. In our earlier work [8], we examined the categorization problem in computer vision, tested some clustering approaches and studied the prototype theory, then we focalized on basic level [1] like a start point of matching like human categorization process.

The rest of the paper is as follows, in the section 2 we present the state of the art concerning the object categorization approaches, in section 3 we develop our approach which consists on the establishment of an evaluation function for object's partitions. In section 4 several applications of this evaluation function will be discussed and an illustration example will be presented in section 5.

2 STATE OF THE ART

If the practical aspect of the categorization is to classify objects into categories, many questions remain, principally the object description, the category representation and the efficient methods of classification. To accomplish our proposed evaluation, it is necessary to know how the categories are formed and under what structures should be organized and how objects are represented to be used in well adapted classification process. Several theories exist and try to guide the practical aspects.

2.1.Categorization theories

The conventional approach assumes the existence of a clear boundary between the categories [9]. With a list of properties or descriptors necessary and sufficient, it is always possible to say that an object belongs to a category or does not. Accordingly, the problem is how to establish this list, knowing that experience has shown its inaccuracy and thus opening a fluctuation around the borders.

As an alternative to this conventional view, many contemporary approaches of cognitive psychology [9][10] in categorization domain based on similarities have been proposed, which the most influential are: the theory of prototypes [11, 13, 22], the exemplar theory [14], the Decision Bound Theory (DBT) [15, 16]. Similarity-based models are able to accommodate seemingly disparate categorization strategies by adjusting similarity parameters to differentially shrink or expand the dimensions of the stimulus space. Some approaches called causal inference approaches or causal models [17, 18, 19] propose to address the categories from another angle than the similarity seen previously. Indeed, recent studies suggest that at least some categories are defined or described by an underlying causal structure [20, 21]: there are relationships between attributes and some properties can affect others. Several theoretical approaches explain the causal inference’s categorization; the two main ones are the associationist approach [22, 23] and the computational approach [17, 19, 24].

2.2.Technical aspect of learning in computer vision

In most domains (e.g. Computer vision), the categories are learned, and all methods refer to research in Machine Learning. The studies focus on Categorization by using similarity-models and leading two different approaches to category learning: generative and discriminative models [25, 26]

Generative and discriminative models are shown as two distinct strategies for estimating the probability that a particular object belongs to a category. Generative learners solve this problem by building a probabilistic model of each category, and then identify which category was most likely to have generated the object (i.e. using Bayes’ rule). Discriminative learners estimate the probability distribution over category labels given objects directly (i.e. Connectionist models) [27].

2.2.1. Category formation

Generative and discriminative models, elaborate a probability “mechanism” to categorization by using a training set of objects that are labeled by known classes or categories. In this case, the techniques of supervised learning are privileged because they establish a relationship between objects and classes. When the objects are not labeled (unknown classes), one solution is to search regularities to construct groups (classes) and formulate a description of each group. The categorization is then to classify objects according to the descriptions. This way is called conceptual clustering developed a machine paradigm for unsupervised learning. Many clustering methods evaluate the partitioning result by using a test set focusing on precision (well fitted objects) and the result can be altered by varying a test set. In computer vision, depending of object representation, class description and the class number, the categorization process can be lent. So, we are invited to review the evaluation to give possibility to adjust partitioning results in a taxonomic tree according to the importance of basic level in prototype theory [1] concerned with visual objects.

2.2.2. Object representation:

In image processing (i.e. road scenes figure1), the object recognition tends to use image content to extract most of the features (descriptors). We can find features related to color [28]: Histograms, color moments, "Joint histograms", Vectors of consistency, "Color correlogram" and others. Other works have also noted that the notion of texture includes visual properties as contrast, granularity, roughness, smoothness, and others. It contains statistical descriptors and others types of descriptors obtained by pre-filtering, using the frequency domain or based on a probabilistic model. It includes two basic models: SAR model (Simultaneous Auto Regressive) [29] and Markov fields [30]. Shape descriptors are widely used in image analysis. We can mention some shape descriptors: convexity, main contour axes, variance, variance elliptical. Points of interest allow extracting shape features locally. They generally include feature extraction algorithm (SIFT, SURF [31]). Some learning methods use other types of features such as HOG, LBP and Haar classifiers [32, 33, 34].

Figure 1: Detection techniques used for different definitions of obstacles considered (source [35]).

3 PROPOSED APPROACH

In object recognition, to optimize the operative effort of comparison, we need to minimize the number of categories. However, this minimization cannot be done without a loss of accuracy. But in this situation, more accuracy lead to more calculations on the recognition level (influence on real time applications: the case of road scenes) and reducing the computation time leads to an inaccuracy on the objects recognition. As clustering methods do not take into account the comparison factor mentioned during the recognition, we propose a measure to evaluate an object's partition, both on the accuracy and the comparative effort. This measure allows to adjust the partitioning process (Clustering) according to the user preference, e.g. accuracy of categories, optimization of recognition or a compromise between them.

In this work, we are inspired by the studies conducted in the context of human categorization (Human visual object categorization) and we consider that the categorization is an effective way to organize a vision system. For this, the internal representation must take into account several levels of abstraction to provide a gradual recognition. Several studies on the categorization process, particularly those of Rosch [1] use three basic levels: the concrete level, the basic level and the upper level.

According to Rosch, basic level is the most important. The terms most commonly used to refer to objects are those corresponding to the basic categories, because in this level:

- Inside a category, there is a maximum of similarities between the members;
- Between categories, we need to have a maximum of differences and get distinctive categories;
- The perception of a similarity is global and the identification is fast;
- The objects most commonly used are first learned.

3.1 Models of categorization process

To operate a categorization process, we must characterize objects by a set of characteristics (technically a feature vector in a given space) and propose a similarity model to assemble similar objects approximately (by comparing characteristics) in categories. Some of the most discussed models in the categorization process are presented in figure 2:

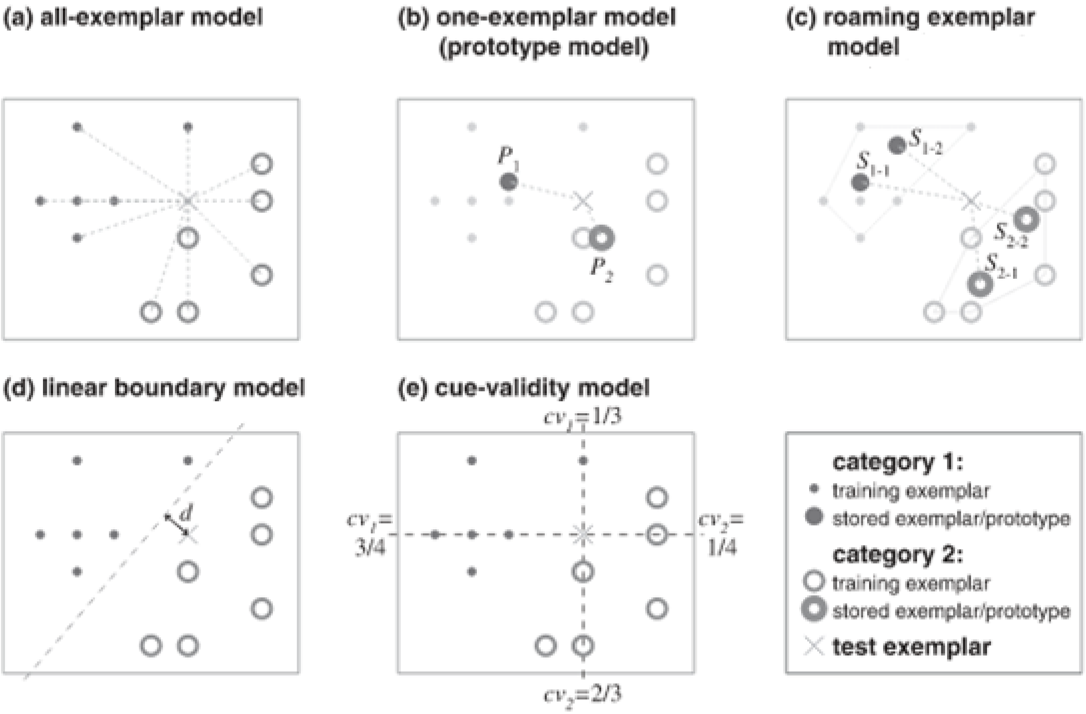


Figure 2: Models of different categorization processes (source [36])

- **Models of exemplars**: associate memory traces (characteristics) of stored exemplars for each category. A category is then represented by a set of exemplars. Several sub types of models differ in the way these stored examples are selected:
  - (Figure 2 --a): all exemplars are representative of the category
  - (Figure 2 --b): prototype, one exemplar is representative
  - (Figure 2 --c): roaming exemplars, some exemplars are chosen as representative

  These models share a mathematical formulation with the classifier « Striatal pattern classifier (SPC) » described by Ashby and Waldron [37, 38].

- **Models of boundary**: decision theory [39] considers that the perceptions of the category are instances of random variables with multivariate normal distributions.
  Thus, the decision limit (where the categories have equal probability densities) is located along the intersection of the curves of probability density surfaces (Figure 2 -- d).

  If the covariance matrices of the exemplars distributions are identical (for two categories for example), then the decision boundary is a linear surface (e.g. A hyper plane); otherwise, it is a quadratic surface. In these models, the categories are represented by their periphery (border) and not by their center as the model prototypes.

- **Models of the Cue-validity**: these models treat each feature (Cue, attribute or trait) as an independent index of belonging to the category, based on the relative numbers of categories examples, which contain a particular value of this attribute.

Combining degrees of validity (frequency of value's similarity, with those of the exemplars) for all attributes constitute the Cue-validity (Figure 2 -- e) and provides a basis for decision. An attribute or property (Cue) therefore has a variable discriminability power for the category.

The Cue-validity is the criteria on which E. Rosch [1] and other researchers (working in the same direction) are based to propose the notion of prototype.

In perception, Cue-validity is often short for ecological validity of a perceptual Cue, and is defined as a correlation rather than a probability. In this definition, an uninformative perceptual Cue has an ecological validity of 0 rather than 0.5.

Formally, the Cue -validity of a feature a_i with respect to category C_j has been defined in the following ways:

- As the conditional probability $p(C_j \mid a_i)$ [40]and [41].
- As the deviation of the conditional probability from the category base rate, $p(C_j \mid a_i)$- $p(C_j)$; Kruschke and Johansen [42].
- As a function of the linear correlation in Busemeyer, Myungand McDaniel [43].
- Other definitions in Restle [44], Martignon and al [45].

Without limiting the generality (we can extend the definition), we consider in this work, a measure for the Cue-Validity which was formulated using a conditional probability (Medin and Schaffer [46]; Nosofsky and Palmeri [47]) that we represent here as:

$$p(Cj|a) = \frac{cardinala(Cj)}{\sum_i cardinala(Cj)} \quad (1)$$

- Where C_j , C_i are categories, and **a** is an attribute.
- $cardinal$**a** (C) is the number of objects of the class C having the same value attribute **a**.

More an attribute is shared by members of the class, more Cue-validity is high. And more Cue-validity is high, more discrimination between objects that belong or not to this category become easier.

Subsequently, we propose several measures based on the approach of Cue-Validity while introducing the entropy as an index of disorder within a set of objects. It permits to build a model of a global function evaluating a given partition. The proposed model, which can be improved according to the formulation of the Cue-Validity and non-linearity, is to combine two antagonistic errors (accuracy and recognition). It is an evaluation function that decide either a partition is the best one or not, in terms of precision and time of recognition.

3.2 Evaluation function of partitions

Here, we formulate our model regardless of the context: Road scene that can be applied to any domain with the same formulation attributes.

We consider that our environment contains a set of objects $\Theta = \{O_1, O_2, O_3, \dots, O_n\}$.

The categorization of the set Θ represents the partitioning operation to obtain the equivalence classes [49]. We note Γ the partition resulting from this operation.

Theoretically, we can consider the taxonomic tree resulting from the lattice of partitions built on the set of objects Θ. Then we can use measures on the partitions to evaluate. In this regard, we proposed a measure which we denote *Ep(*Γ*)*, which expresses the non-homogeneity of the characteristics in the categories. By minimizing *Ep(*Γ*)* we build the highest possible homogeneous categories. This measure decreases each time we move down on the tree.

We propose a new measure notes *Ep(*Γ*)*, which expresses the non-uniformity of properties in categories. Minimizing *Ep(*Γ) consist on building the highest possible homogeneous categories. This measure decreases every time we go down in the tree.

On the other hand, recognition must be fast. It is therefore necessary to climb up the tree before the matching process.

Higher you go, the more the uncertainty of finding a category for an object decreases, the top of the tree contains all objects. We note *Ec(*Γ*)* the measure that expresses the uncertainty of categories.

For that we can say, that to allow the operation of recognition to succeed in the majority of cases on a quick and robust way, we must find a partition that achieves the minimum of *Ep(*Γ*)* and *Ec(*Γ*)*.

We are then faced with a conflict situation: to minimize *Ep(*Γ*)* we go down on the tree and to minimize *Ec(*Γ*)* we climb the tree. Thus, we need a compromise by combining the two measures.

We note *E(*Γ*)* this combination, formulated as follows:

$$E(\Gamma) = \alpha.Ep(\Gamma) + \beta.Ec(\Gamma) \quad (2)$$

Where α and β are parameters to adjust the partition using experimental data depending on the degree of expertise in a specific field. Indeed, the base level for an expert is deeper in the tree than a non-expert in a given field. These parameters actually express the importance given to the induction and prediction in a categorization operation.

3.2.1 Uncertainty about the attributes*: Ep(*Γ*)*

In information theory, uncertainty is the amount of unknown information in a signal.

Shanon [48] provided a measure of the uncertainty information based on the entropy of the probability distribution:

$$H = -\sum_{i=1}^{s} pi.\log_2(pi) \quad (3)$$

$$pi \geq 0$$

$$\sum_{i=1}^{s} pi = 1$$

Note that:

- If there is only one category, the uncertainty is zero (H =0; category i, pi =1, pj =0 si i≠j)
- H is much larger than the categories are equiprobable
- H is $\log_2(s)$ when s categories are equiprobable
- Unit: the information bit

We remind that $\theta = \{O_1, O_2, \dots, O_n\}$ is our set of objects.

Each object is described by a set of attributes whose values can be one-dimensional, multi-dimensional (case of images) or even data structures.

Let's put $A = \{a_1, a_2, a_3, \dots, a_m\}$ the set of attributes of Θ.

Attributes have domains of possible values: $D_{ai}, D_{a2}, \dots, D_m$

With $D_{ai} = \{v_{1i}, v_{2i}, v_{3i}, \dots, v_{mi}\}$ $cardinal(D_{ai}) = m_i$

We note C_k a category in a partition Γ of *N* categories.

Let's put n_{ai}^{j} the number of objects having j^i attribute value of a_i in the category C_k

Let's put $p_{ai}^{jk} = \frac{n_{ai}^{j}}{cardinal(C_k)}$ (4) probability of j^i value of a_i in the category C_k

It is then possible to generate a probability distribution of all the attribute values of a_i :

$$F_{ik} = \{p_{ai}^{1k}, p_{ai}^{2k}, \dots, p_{ai}^{mik}\} \quad (5)$$

The entropy of the distribution:

$$H(F_{ik}) = -\sum_{j=1}^{mi} p_{ai}^{jk} . \log_2(p_{ai}^{jk}) \quad (6)$$

$H(F_{ik})$ defines the uncertainty of the attribute a_i. It expresses how values of a_i are distributed in C_k

Uncertainty about all attributes will be the sum of the uncertainties in the category C_k .

We call this uncertainty $E_{pc}(C_k)$.

We have then: $E_{pc}(C_k) = \sum_{i=1}^{m} H(F_{ik})$ (7)

Since *n* is the total number of objects and N is the number of categories, we also have:

$$n = \sum_{k=1}^{N} Cardinal(C_k) \quad (8)$$

The measure of uncertainty *Ep(*Γ) of the partition Γ is defined as the average of the uncertainties concerning categories of membership of any object. O_i

Let's put $f(O_i) =$ category of the object O_i then:

$$E_p(\tau) = \frac{1}{n}\sum_{i=1}^{n} E_{pc}(f(O_i)) \quad (9)$$

Objects of the same category C_k have an identical *Epc* and they are *cardinal(C*$_k$*)*, *Ep(*Γ*)* is then :

$$E_p(\tau) = \frac{1}{n}\sum_{k=1}^{N} cardinal(C_k) . E_{pc}(C_k) \quad (10)$$

3.2.2 Uncertainty about the categories: *EC(*Γ)

Let's put A set of all attributes, and P(A) the set of its parts. We denote A' as a part of A,

Let's consider $ap(O_i, C_k, A')$ the function that returns the number of identical objects to O_i in the category C_k depending on the attributes contained in A' .

We define a probability of the object matching (how the object O_i belong to C_k with A'):

$$p_{ap}(O_i, C_k, A') = \frac{ap(O_i, C_k, A')}{\sum_{j=1}^{N} ap(O_i, C_j, A')} \quad (11)$$

So we have a probability distribution of categories of the couple object (O_i, A'):

$F(O_i, A') = \{p_{ap}(O_i, C_1, A'), \dots, p_{ap}(O_i, C_N, A')\}$ (12)

The uncertainty is then: $E_{cc}(O_i, A') = H(F(O_i, A'))$ (13)

Uncertainty on categories *Ec(Γ)* is an average of Ecc (by considering all parts of *A* and all the objects). If some parts are more interesting than others, we can introduce a probability $ps(O_i, A')$ and we have:

$$E_c(\tau) = \frac{1}{n}\sum_{i=1}^{n}\sum_{A'\in P(A)} ps(O_i, A') \,.\, E_{cc}(O_i, A') \quad (14)$$

To simplify, we can use the equiprobability:

$$ps(O_i, A') = \frac{1}{cardinal(P(A))} = \frac{1}{2^{cardinal(A)}} = \frac{1}{2^m} \quad (15)$$

We have a simplified version of *Ec(Γ).*

$$E_c(\tau) = \frac{1}{n} \cdot \frac{1}{2^m}\sum_{i=1}^{n}\sum_{A'\in P(A)} E_{cc}(O_i, A') \quad (16)$$

4 APPLICATIONS AND DISCUSSION

Ec and *Ep* have antagonistic roles. The root of the tree has only one category, the effort focuses on the attributes, in this case we keep only *Ep*. Otherwise, in the leaves (each object is a category), the effort focuses on the categories: we retain only *Ec*. For this we choose $\beta = 1-\alpha$. $0 \leq \alpha \leq 1$, and we have: $E = \alpha Ep + (1-\alpha)Ec$.

The basic level is closer to the root or leaf depending on the value of α. In fact, this parameter expresses the degree of expertise in the area of objects. The more we have the knowledge, the closer we are to the tree leaves value of α approximate 1.

Several procedures of categorization can be proposed in an incremental way with every step the overall uncertainty *E* is minimized. For example, we can consider here the general appearance of such procedure:

An object *O* is represented by a vector of attributes: $O = (v_{x1}, \ldots, v_{zm})$
Where v_{ji} is the value of the attribute a_i located in the row *j* in D_{ai} (Values domain).

The idea of the algorithm is to find the optimal partition to minimize the total uncertainty by a progressive construction of this part. We start from a small agglomeration of some objects made necessary for the uncertainty calculation.

We proceed by adding objects to an existing agglomeration and we decide whether to merge categories or to divide them.

The search for an object category is realized by minimizing the global uncertainty *E (Γ).*

It is also possible to integrate the measure in mixed classifications: to begin with a preliminary partitioning (dynamic cloud, mobile centers,…) and continue by ascending hierarchical classifications using dendrogram cuts [50]. Minimizing *E(Γ)* allows to choose the right cut and therefore the correct partition.

Some other uses of uncertainty will be considered in the example presented in section 5:

- Evaluation of incremental classification algorithms: in this case, we try to get the best partition based on objects (characterized by descriptors operated on certain types of images…), by experimenting several existing algorithms (kmeans, fcm,…)
- Construction of the taxonomic tree: Theoretically the basic level mentioned by Rosch can be obtained for α = ½, but this basic level can vary depending on the expertise of the domain

user. Variation of α can build many levels, including the upper level (α =0), the concrete level (α =1). We will then have a taxonomic tree.

- Determination of the set of attributes that determines the best categorization: in the evaluation of *Ec* we use all parts of the attributes set. The minimization of *E* is also achieved through a subset of attributes considered as dominant in the categorization. This subset will be considered as the most important set of attributes to discriminate between categories.
- Adaptation to a multi-dimensional attributes: (Points of Interest) through statistical transformation.
- Support for multiple definitions of the Cue-Validity.

5 EXAMPLE: CATEGORIZATION OF ROAD PANELS

5.1 Experimentation

We applied our evaluation function on the categorization of panel signs. We selected a set of 81 panels to work with including of 4 types of panels (prohibition, danger, intersection, indication) as shown in the following table.

Table 1: Panels distribution according to their classes

Sample	Prohibition	Danger	Intersection	Indication	Total
Number of panels	37	25	9	10	81
Percentage	45,68%	30,86%	11,11%	12,35%	100,00%

The first step is the object characterization and the descriptors extraction, for a numerical representation in order to classify them. We selected three types of characteristics for these objects (panels): shape, color and texture. Each characteristic is represented by a set of features (descriptors) calculated using a set of functions in Matlab [52]. We have chosen to keep the most relevant features (figure 3) for each characteristic.

To extract features concerning texture, we used an algorithm based on Gray-level co-occurrence matrix (*GLCM*) by calculating 14 Features. We selected the following five:

- Entropy ($\mathbf{F_1}$): a statistical measure of randomness. It characterizes the degree of organization.
- Contrast ($\mathbf{F_2}$) measuring the local variation of the co-occurrence matrix of gray level.
- Correlation ($\mathbf{F_3}$) measuring the joint probability of occurrence of specified pairs of pixels.
- Energy ($\mathbf{F_4}$) providing the squares sum of *GLCM* elements. Also known as uniformity or the angular second moment.
- Homogeneity ($\mathbf{F_5}$) Measures the closeness of element distribution in the GLCM to the GLCM diagonal.

For the shape characteristic we used the predefined function regionprops, which provides a set of measures (area, perimeter, connected-pixel regions...) after binarization. From this function, we selected 5 features:

- Area ($\mathbf{F_6}$): the number of pixels in the region
- Perimeter ($\mathbf{F_7}$): the perimeter of the distance between each adjacent pair of pixels around the region borders.
- Convex area ($\mathbf{F_8}$) the scalar which indicates the number of pixels in Convex Image. This property is supported only for 2-D for input label matrices.

- Euler number (**F_9**): The scalar which indicates the number of objects in the region, less the number of holes in objects.
- Extent (**F_{10}**): scalar that specifies the number of pixels in the pixel region of the total area delimitation. Calculated as divided by the area of the bounding box area. This property is supported only for 2-D input label matrices.

With regard to the color characteristics, we used an implementation of the method described by A. Weijer [51]. It is based on the calculation of the energy derived from (Gaussian) with a tensor colors projected by two structures: "star" and" circle".

We built 2 features:

- Moment of second degree (**F_{11}**): on the calculation of the energy derivatives, according to star structure.
- Moment of second degree (**F_{12}**): on the calculation of the energy derivatives, according to circle structure.

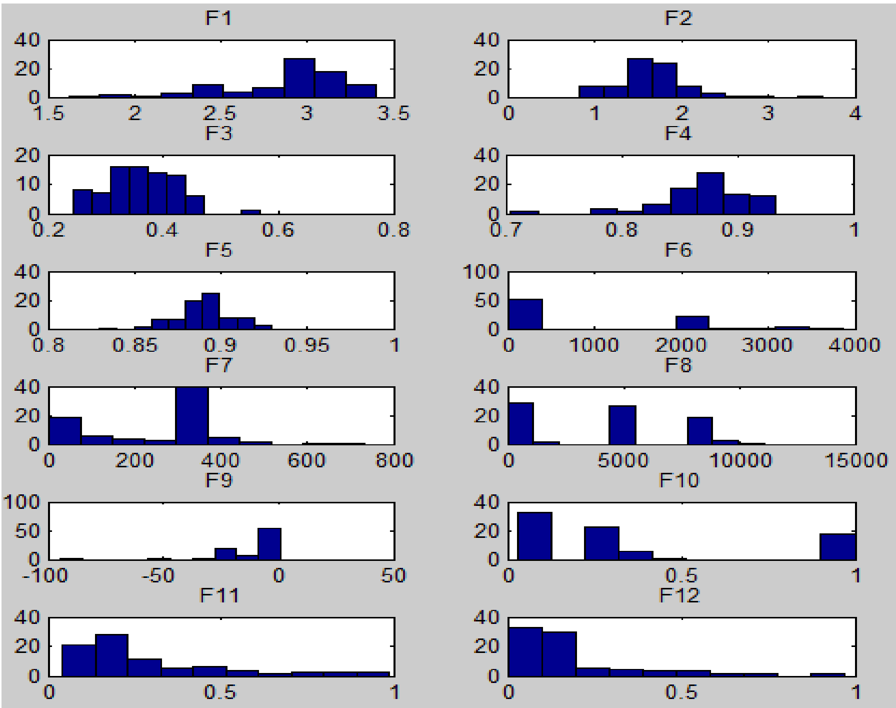


Figure 3: Distribution of the descriptors values on the set of objects

The taxonomic tree generation steps are described in figure 4:

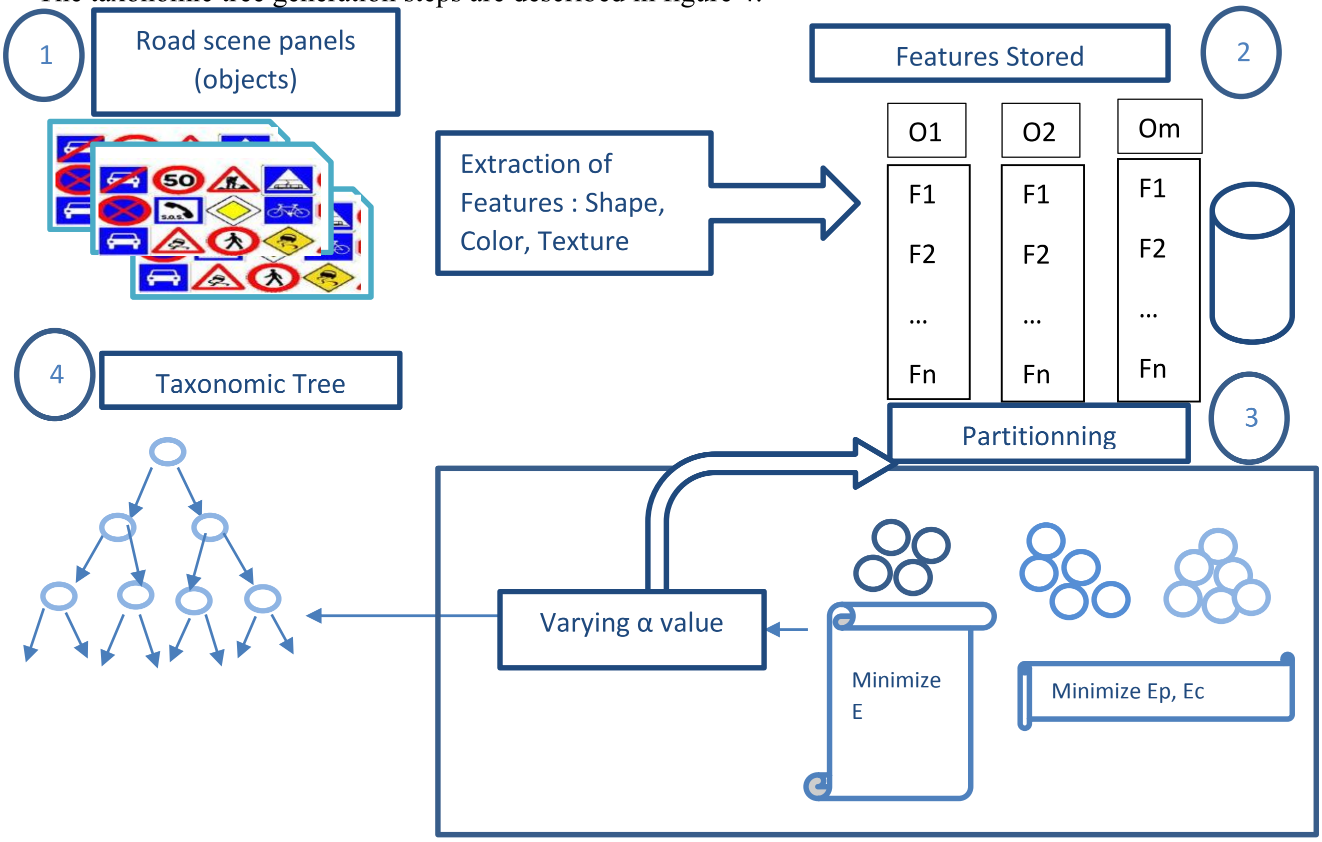


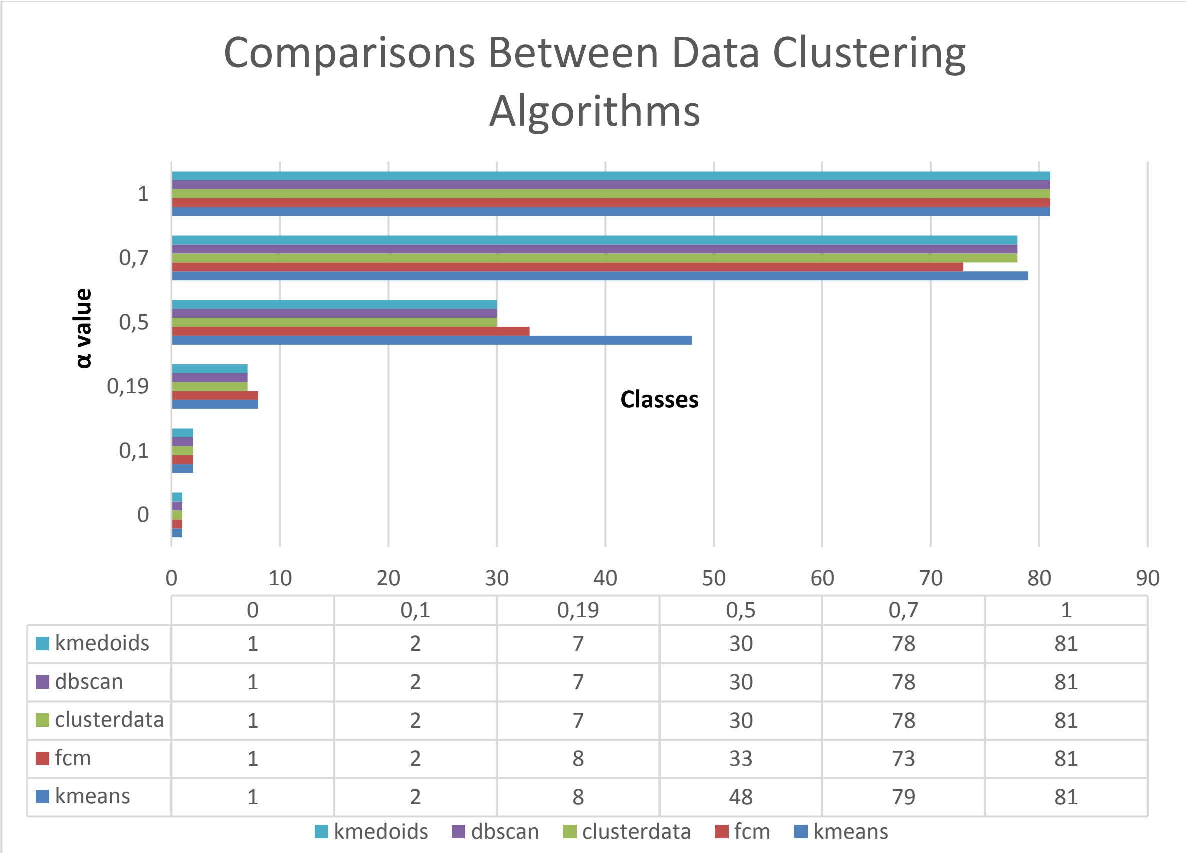
Figure 4: Steps for generating a taxonomic tree

- ✓ Step 1: Comparison of Clustering Algorithms

We compared between the different classifications obtained by different clustering designed to divide a set of homogeneous packet data by minimizing the intra-class inertia and maximizing the interclass inertia.

We have chosen the algorithms: kmeans, fcm, clusterdata, dbscan, and kmedoids. [MATLAB 2012]

The figure 5 shows the different partitioning obtained for **α** values in the interval [0,1].



	0	0,1	0,19	0,5	0,7	1
kmedoids	1	2	7	30	78	81
dbscan	1	2	7	30	78	81
clusterdata	1	2	7	30	78	81
fcm	1	2	8	33	73	81
kmeans	1	2	8	48	79	81

Figure 5: Results of the partitions obtained with the clustering algorithms (Kmeans, fcm, Clusterdata, Kmedoids, dbscan)

The approach consists on applying a classification method iteratively for the number of classes. We keep only the partition with the highest score based on our evaluation function (by mean to minimize the *E* uncertainty). The figure below shows the evolution of $E(\Gamma)$ (on green the best partition Γ with n classes. $Ep(\Gamma)$ and $Ec(\Gamma)$are shown in red and blue respectively). The evaluation is made with a fixed value of Γ.

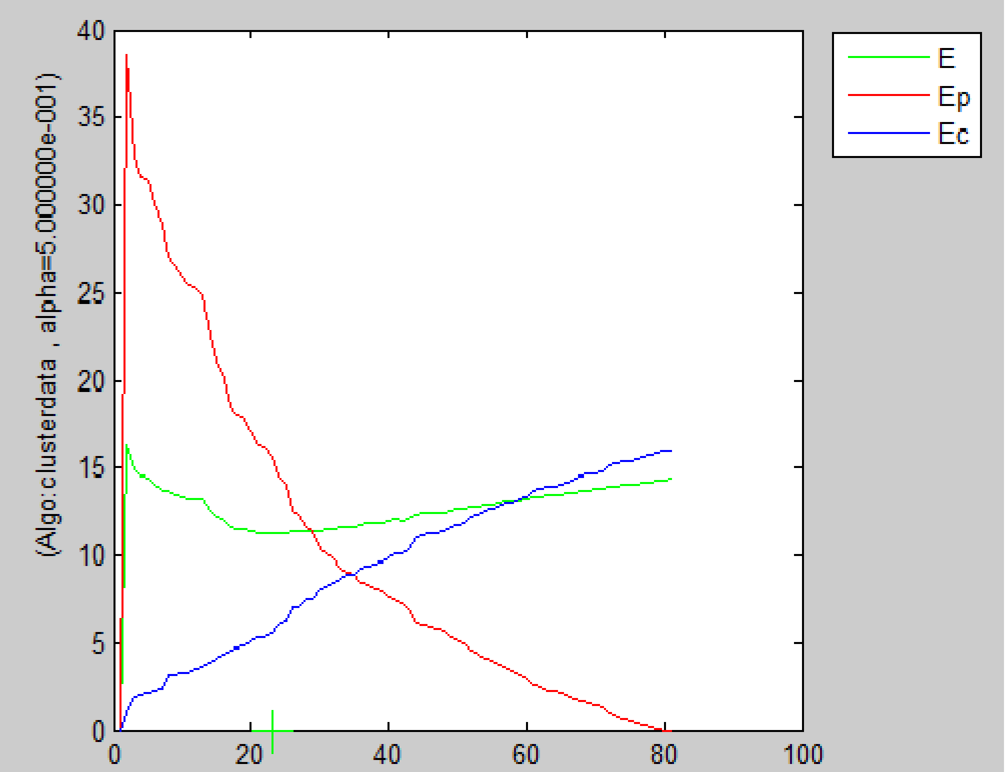


Figure 6-a: uncertainty Graphs with Clustering algorithms clusrterdata for α=0.5

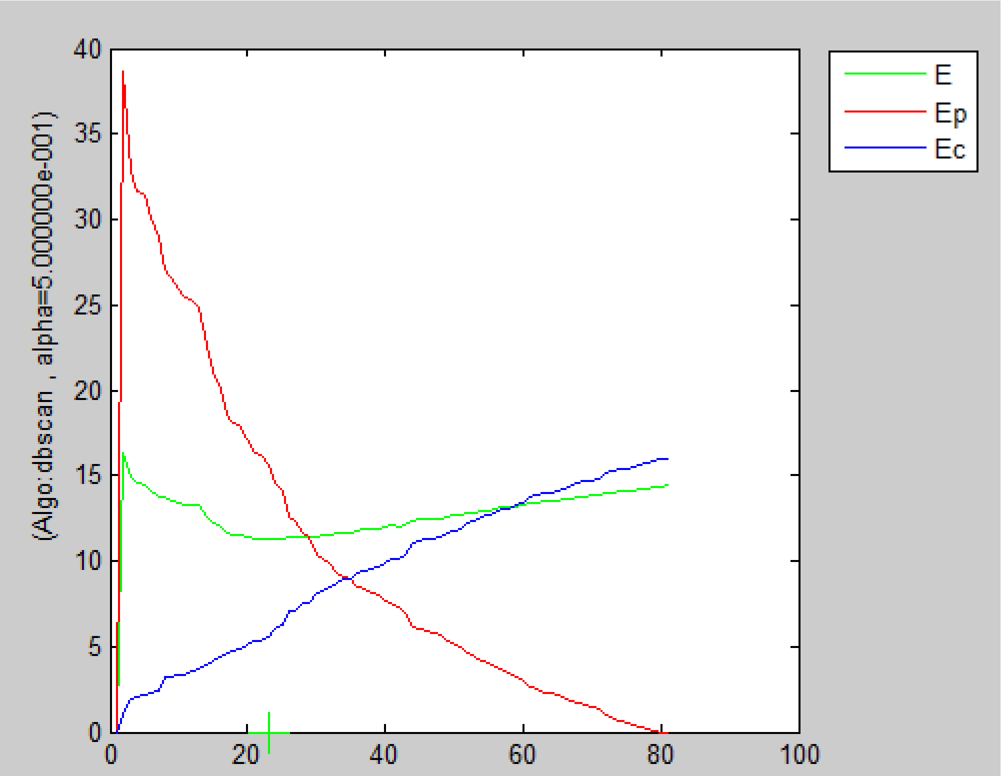


Figure 6-b: uncertainty Graphs with Clustering algorithms dbscan for α=0.5

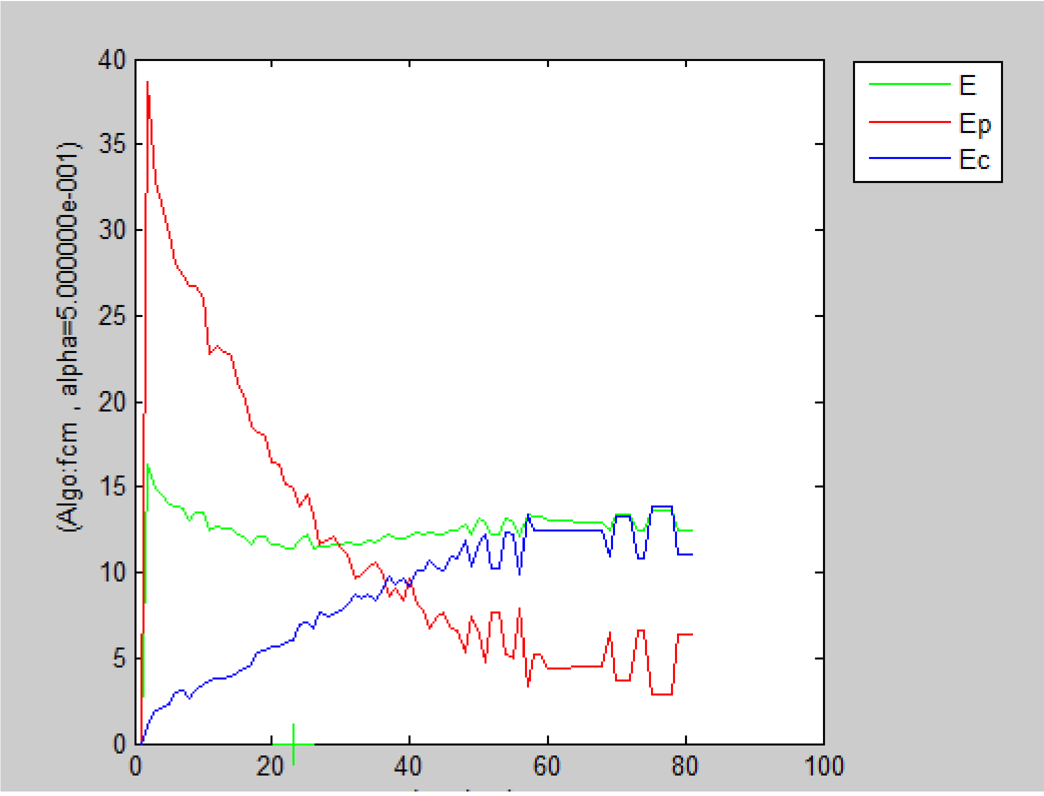


Figure 6-c: uncertainty Graphs with Clustering algorithms fcm for α=0.5

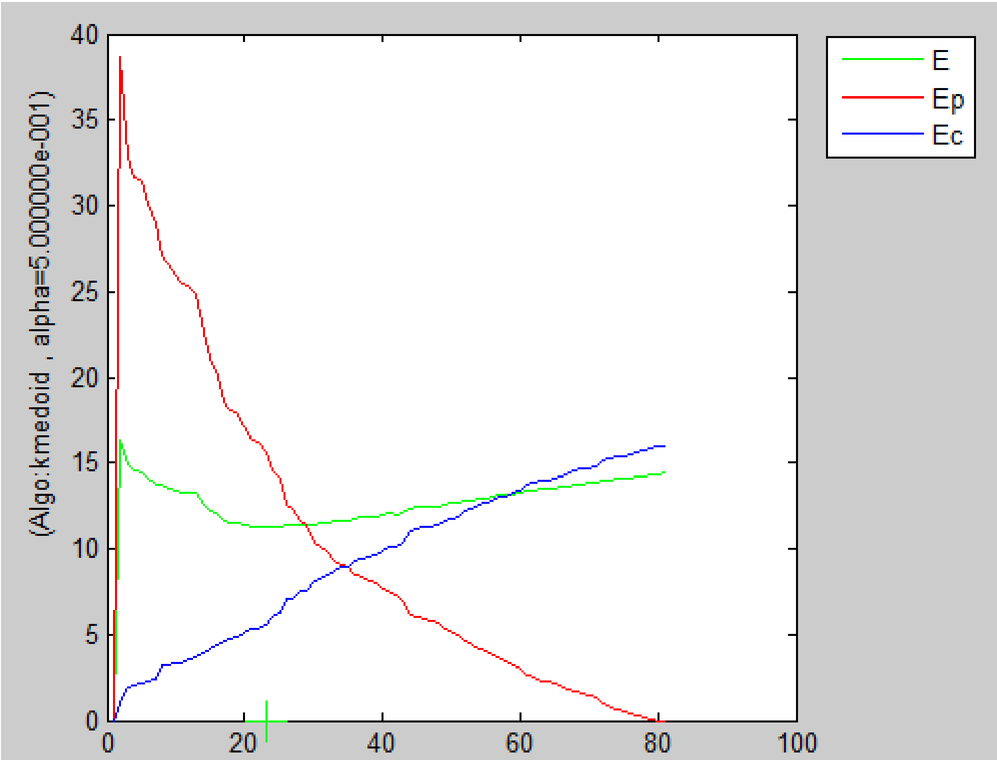


Figure 6-d: uncertainty Graphs with Clustering algorithms kmedoids for α=0.5

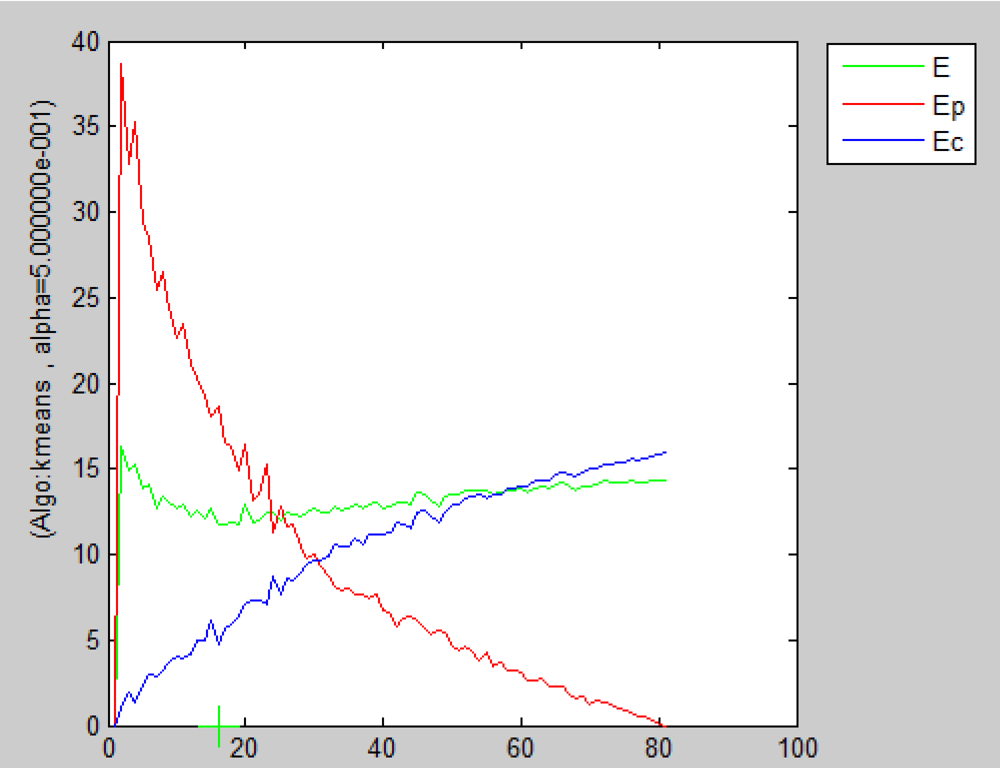


Figure 6-e: uncertainty Graphs with Clustering algorithms kmeans for α=0.5

To generate taxonomic tree (following the steps in Figure 4), we chose the Kmeans algorithm and a set of **α** values. If we desire to have a tree with 6 levels, we chose 6 values in the range [0, 1]. The figure 7 shows an example of a tree with 6 levels. Each level is a partition (it has a set of classes and each class has a set of objects: traffic signs are used in this case), a class of lower level objects may contain more than a top-level class.

α = 0	1 class
α = 0,1	2 classes
α = 0,19	8 classes
α = 0,5	48 classes
α = 0,7	79 classes
α >= 0.9	81 classes

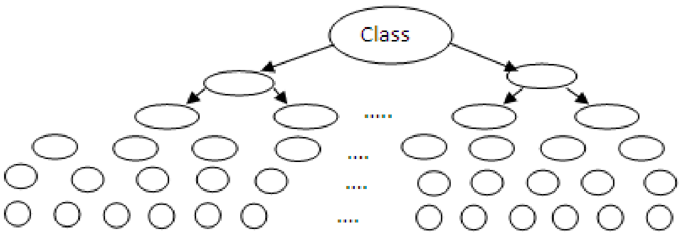


Figure 7: taxonomic tree (kmeans algorithm)

Examples (Figure 8) of images on two classes of panels (α =0.1) with kmeans:

Images of the first class Images of the second class

Figure 8: A partition of two classes (object images)

✓ Step 2: Evaluation of our classification using the confusion matrix

The evaluation of classifiers is an essential step of supervised learning. We have built a predictive model, and we want to measure its performance. From there, we opted for the confusion matrix and related indicators, which are very popular in machine learning research. This is a contingency table comparing the obtained classes and actual classes in the sample, used to measure the quality of a classification system.

In Table 2 we put the real classes (indication, danger, intersection and Prohibition) and the 4 classes obtained by this function using the kmeans algorithm with α=0.14.

Table 2 : Confusion matrix

	Resulting Classification				
	Prohibition	Danger	Intersection	Interdiction	
Real Classification	Class 1	Class 2	Class 3	Class 4	Total
Class 1	2	5	0	3	10
Class 2	0	17	3	17	37
Class 3	0	0	0	9	9
Class 4	2	1	0	22	25
					81

Table 3: Confusion matrix indicators

Error rate	0,0617284
Recall	0,2
Precision	0,5
False positive rate	0,08
Specificity	0,92

Definitions of the confusion matrix indicators:

- The error rate is the proportion of misclassified; it estimates the probability of misclassifying an individual chosen randomly from the population when the prediction model is applied.

- Recall (also called: sensitivity or true positive rate-TVP) is the fraction embedded in the target (the target are individuals who were classified as positive by the model) positive.
- The precision is the proportion of positive within the target.
- The false positive rate is the fraction of negatives that have been integrated into the target.
- Specificity is the proportion of negatives which are excluded from the target.

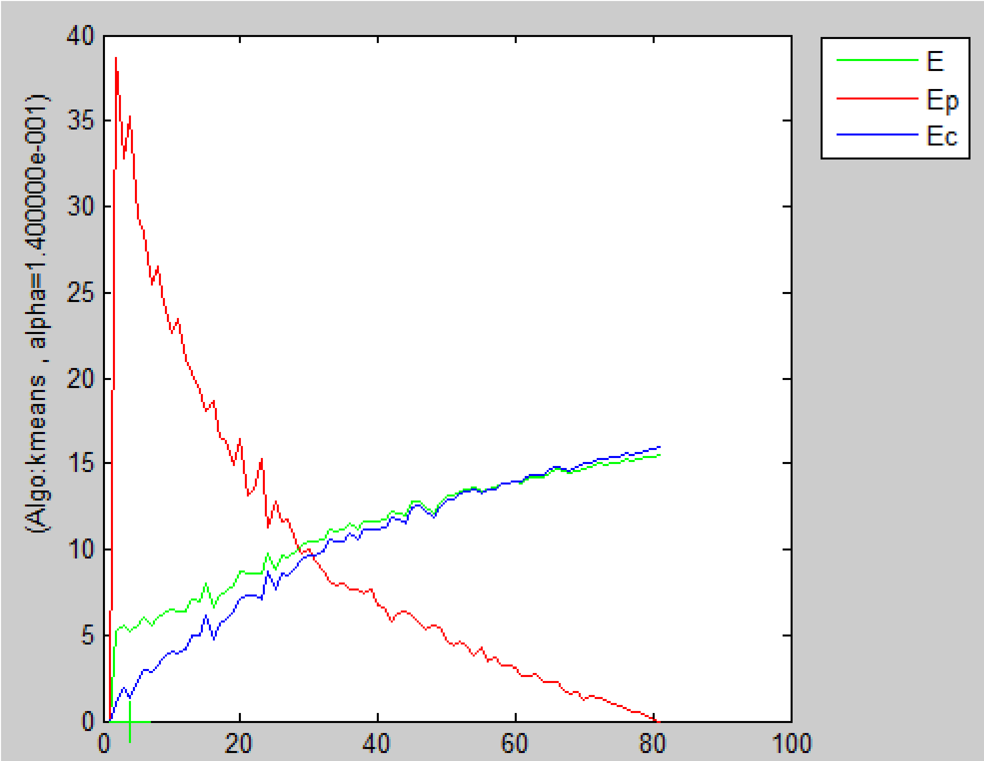


Figure 9: Uncertainties Graph kmeans α=0.14 with the minimum uncertainty, E=1.576821

We have also worked with another images' bases (20 images) which contains different vehicles' shapes that we tried to classify. We used the sames features of color, shape and texture. Table 4 shows the results of this example.

Figure 10: Some vehicles images from the set of objects

Table 4: Results of the partitions obtained with the clustering algorithms (Kmeans, fcm, Clusterdata, Kmedoids, dbscan) on a vehicles set of objects

	kmeans	fcm	clusterdata	dbscan	kmedoids
0	1	1	1	1	1
0,1	3	3	3	3	3
0,12	4	3	4	4	4
0,16	6	7	6	6	6
0,2	14	12	14	14	14
1	20	20	20	20	20

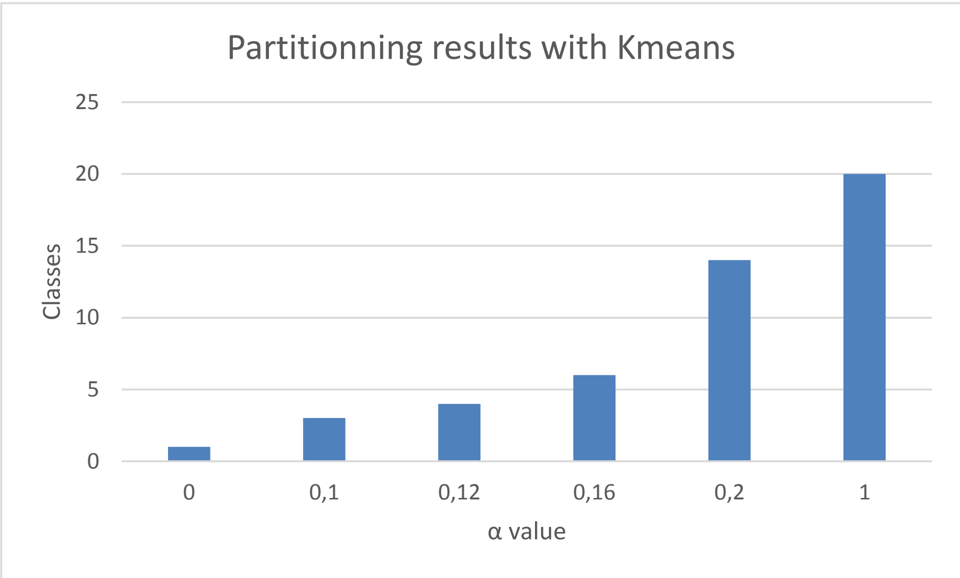


Figure 11 : Obtained partitions with kmeans

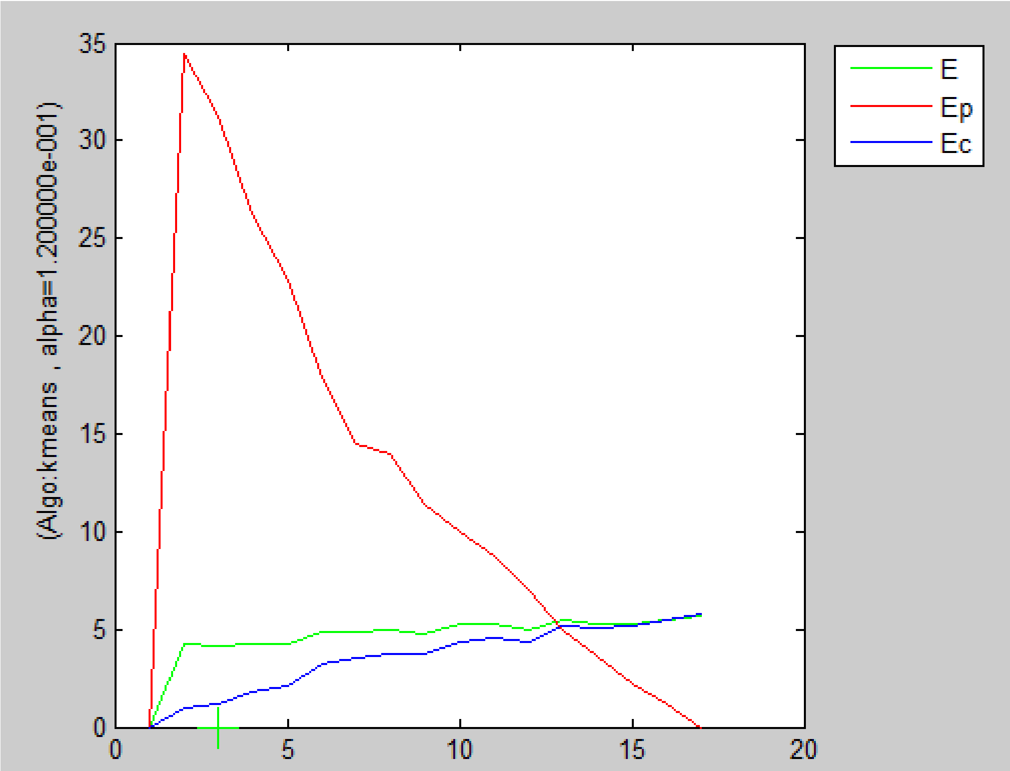


Figure 12: Uncertainties Graph with kmeans and α=0.12

5.2 Results analysis

Figures (from 6-a to 6-e) show the expectations from the uncertainties Ep (decrease) and Ec (increase) when the number of classes increases. We can also notice that for a fixed value of α, different algorithms provide a partition minimizing the uncertainty E with practically the same number of classes. Theoretically, the compromise for the minimization of the uncertainties average Ep and Ec is searched for α=1/2. This result depends also on the quality of the descriptors, in our example the color and the shape are more interesting than the texture (F1 to F6), which influence the search for the compromise. Color descriptor is not well represented (just two Features F11 and F12) however the texture is represented with more features (F1 to F6) which influence the compromise search. Indeed, with the descriptors used the actual number of classes (4) was found for α =0.14 and not with α=0.5, favoring instead the matching effort. Another example (figure 10) has been studied on a vehicle image database, Confirmed these findings.

The taxonomic tree, provided by varying the α value, allows for the moment to fix an appropriate level according to an expert in the field with a pronounced error (Ep) on the accuracy. In our case, the level of 4 classes obtained by kmeans mentions a quite high Ep because of the chosen descriptors, there is unnecessary texture descriptors. This explains, in part, the bad ratios derived from the confusion matrix because actual classes were selected semantically and are based on the shape and color. However, By cons, good results were obtained for two-level classes (figure 8).

6 CONCLUSION

In this paper, we addressed a fundamental problem in image processing and object recognition. This is to provide a measure to establish a good categorization of objects. This leads to many uses like the establishment of the taxonomic tree of objects as a basis for the object organization in vision systems. The problem of object recognition is a difficult problem that has been included in the proposed evaluation function by adjusting the basic level recommended in the Rosch's work. Moreover, it is possible to determine the most appropriate clustering method according to the field and the type of used images as shown in our example.

In the next work we plan to test other models of probabilities in the Ep and Ec definition. Then we strive to provide a global scheme (automatic process of the taxonomic tree construction) as a basis for the establishment of the ontologies in vision systems by field of application.

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