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Multi-level Image Classification Using Fuzzy Petri Net

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Abstract— For a multi-level image classification, a knowledge representation scheme based on Fuzzy Petri Net with fuzzy inference algorithms is used. A simple graphical Petri net notation and a welldefined semantics displaying the process of reasoning through inference trees are used for visualization of the knowledge base and explanations of derived conclusion. Used knowledge representation formalism has the ability to show a probability of concepts and relations. The procedures of image multi-level classification using fuzzy recognition and inheritance algorithms on a knowledge representation scheme, as well as experimental results of image semantic interpretation, are presented.

Keywords— Fuzzy Petri Net, Image Classification, Knowledge Representation

I. INTRODUCTION

Digital images have become unavoidable in the life of modern people. The number of digital images on a specialized web site counts in millions, and private and business collections are rapidly increasing. A large number of images is becoming a current problem for search and retrieval, as well as for organizing and storing.

It is believed that we could retrieve and arrange images simply if they can be automatically annotate and describe with words that are used in an intuitive image search. People for the interpretation of the images usually do not use objects that appear in the image, but the broader context that arises from the relation between these objects and scenes. However, the content of images is generally difficult to typify, and sometimes is not even easy to describe the images in words that will meet different requirements and needs.

To interpret image as people do, feature extraction and recognition of objects are not sufficient. A multi-level classification, semantic modeling and representation of knowledge that is specific to the application domain are necessary. Thus, the process of multi-level image classification should include low-level image features extraction, then learning and implementation of a model that maps image features to classes that can be recognized in the image and a knowledge acquisition to determine the parent classes. The amount of knowledge that is needed for the classification of images increases with the semantic level of concepts used to interpret the images.

For solving the problem of object recognition many different approaches has been used. A recent survey and research made in the field can be found in [1]. For multi-level image classification and interpretation several different approaches that use machine learning techniques or models for knowledge representation and reasoning were proposed in recent years and hereafter we will mention some of them.

In [2] a Multi-Level Image Sampling and Transformation methodology (MIST) is described that uses a neural network as a classifier and symbolic rules from the knowledge base in order to semantically interpret a new image.

A hierarchical model for generating words that correspond to class labels is proposed in [3]. The model is inspired by the Hofmann's hierarchical clustering model and a model of soft clustering.

In [4] a SVM classifier is used for learning the elementary classes of natural scenes, which are then using probabilistic model linked in concepts of a higher semantic level, such as "beach".

To view the perceptual and semantic information of multimedia content a semantic network is used in [5].

One of the early works that uses the ontology for the semantic description of the image content and descriptive logic for verification of the classification results is [6].

To explore the ontology of words that is used for image interpretation and annotation [7] have used WordNet. This idea is further extended in [8]. The authors intend to create public image ontology, the ImageNet, with aim to illustrate each of the concepts from the WordNet ontology with 500-1000 images.

Within the project aceMedia, [9] combine ontology with fuzzy logic to generate concepts from beach domain with appropriate reliability. In [10], the same group of authors have used the SVM classifier and inference engine that supports fuzzy descriptive logic and in [11] a combination of different classifiers for learning concepts and fuzzy spatial relationships. Authors have reported that environment used by the ontology is shown to be incompatible with that of fuzzy reasoning engines.

In this paper, for multi-level image classification, a knowledge representation scheme based on Fuzzy Petri Net is used. A knowledge formalism and inference engine is briefly presented in chapter two. A proposal of multi-level image classification is given in the third chapter. An example of knowledge base, which relates to outdoor domain, is shown in chapter four. Furthermore, a description of derived conclusion using inheritance and recognition trees, as well as experimental results is given in chapter five, six and seven, respectively.

II. Knowledge Formalization

For multi-level image classification a knowledge representation scheme based on Fuzzy Petri Net, named KRFPN, [12] is used.

A. Definition of Knowledge Representation Scheme

The KRFPN scheme is defined as 13-tuple:

KRFPN = (P, T, I, O, M, Ω, μ, f, c, α, β, λ, Con), (1)

where:

$P = \{p_1, p_2 ... p_n\}$, $n \in \mathbb{N}$ is a set of places,
$T = \{t_1, t_2 ... t_m\}$, $m \in \mathbb{N}$ is a set of transitions,
$I: T \rightarrow P^{\infty}$, is an input function,
$O: T \rightarrow P^{\infty}$, is an output function,
$M = \{m_1, m_2 ... m_r\}$, $1 \leq r < \infty$, is a set of tokens,
$\Omega: P \rightarrow P(M)$, is a tokens' distribution within places,
$\mu: P \rightarrow N$, marking of places,
$f: T \rightarrow [0, 1]$, the degree of truth of the transitions,
$c: M \rightarrow [0, 1]$, the degree of truth of the token,
$\alpha: P \rightarrow D$, maps place from set P to concept from set D,
$\beta: T \rightarrow \Sigma$, maps transition from set T to relation in set Σ,
$\lambda \in [0, 1]$, threshold value related to transitions firing,
$Con \subseteq (D \times D) \cup (\Sigma \times \Sigma)$, is a set of pairs of mutually contradictory relations or concepts.

The KRFPN can be represented by a direct graph containing two types of nodes: places and transitions. Graphically, places $p_i \in P$ are represented by circles and transitions $t_j \in T$ by bars. The relationships, based on input and output functions are represented by directed arcs. In a semantic sense, each place from set P corresponds to a concept from set D and any transitions from set T to relation from set Σ (Fig. 1).

A dot in a place represents token $m_1 \in M$, and the place that contains one or more tokens is called a marked place. Tokens give dynamic features to the net and define its execution by firing an enabled transition. The transition is enabled when every input place of transition is marked, i.e. if each of the input places of the transition has at least one token. Moreover, if threshold value λ that defines the sensitivity of the knowledge base is set, truth value $c(m_1)$ of each token must exceed the value of λ if the transition would be enabled.

An enabled transition t_j can be fired. By firing, a token moves from all its input places $I(t_j)$ to the corresponding output places $O(t_j)$. In Fig. 1 there is only one input place for transition t_j, $I(t_j) = p_i$ and only one output place $O(t_j) = p_k$. After transition firing, a new token value $c(m_2)$ is obtained as $c(m_1) * f(t_j)$ in the output place (Fig. 2). Values $c(m_1)$ and $f(t_j)$ are degrees of truth assigned to token at the input place $p_i \in I(t_j)$ and transition $t_j \in T$, respectively.

Value of $c(m_1), f(t_j) \in [0,1]$, can be expressed by truth scales where 0 means «no true» and 1 «always true» [13]. Semantically, value $c(m_1)$ express the degree of uncertainty of joining a particular concept form set D to place p_i, and value $f(t_j)$ the degree of uncertainty of links between relationship from a set Σ and a transition t_j.

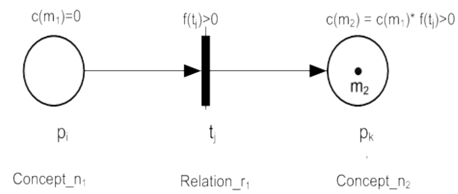

Fig. 2 Fuzzy Petri net formalism with associated semantic meaning

B. Inference Engine

Inference engine of KRFPN scheme consists of three automated reasoning processes: fuzzy inheritance, fuzzy recognition and fuzzy intersection.

All inference processes are based on dynamic properties of the network, and are graphically shown by the inheritance or the recognition tree. The steps of all algorithms are given in [12].

This paper describes the use of fuzzy inheritance and fuzzy recognition algorithms for multi level image classification.

III. Image Semantic Categories

The goal is to classify images as much as possible closer to the semantic concepts that people use when interpreting these images. Therefore, proposed multi-level image classification includes classes from four semantic levels – an elementary class, a generalization class, a derived class and a scene class. Elementary classes correspond to object which were directly identified in the image like "train", "airplane" or "sky".

Other semantic class categories are used for the interpretation of images on higher-level and are defined according to expert knowledge. Generalization classes include classes which were created by generalizing objects recognized in the image or in the case of high-level generalization by generalizing already generalized classes like: "airplane" (elementary class) - "vehicle" (generalization of elementary

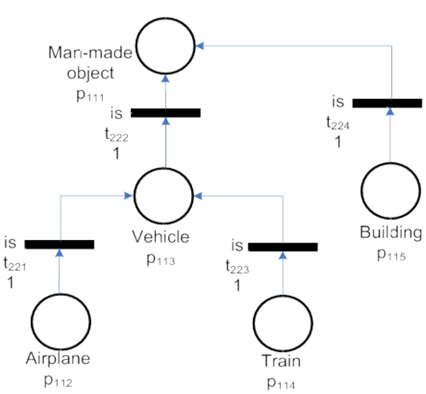

Fig. 3 A part of knowledge base displaying class generalization

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class) – “man-made object”(high-level generalization), Fig 3.

Same abstract classes that are “common” to human interpretation of some objects like “winter” for “snow” can be described by derived classes.

Scene classes are used to represent the semantics of the whole image like “mountain view”, “natural scene”, “outdoor”.

IV. Knowledge Base Definition

A. *Definition of Concepts*

According to the KRFPN scheme, classes from all semantic levels are elements of a set D, where D = D1 ∪ D2 ∪ D3. A subset D1 includes generalized classes (e.g. set GC ={Outdoor Scenes, Natural Scenes, Man-made Objects, Landscape, Vehicles, Wildlife, …}), scene classes (e.g. set SC ={Seaside, Inland, Sea, Underwater, Space, Airplane Scene, Train Scene, …}) and related derived or abstract classes (e.g. set AC ={Summer, …}) defined according the expert knowledge, thus $D_1 = SC \cup GC \cup AC$.

A subset D2 is used in case of some special instance of classes of interest or for instance of unknown class X that should be determinate.

A subset D3 represents class attributes and in this experiment consists of elementary classes like C = {Airplane, Train, Shuttle, Building, Road, Grass, Ground, Cloud, Sky, Coral, Dolphin, Bird, Lion, Mountain, …} that are according to modified Bayesian rule selected as attributes of scenes. It is assumed that a scene may contain several characteristic elementary classes, so instead of choosing an attribute with a maximum posterior probability, all those elementary classes with a posterior probability $P(SC_i|C_k), \forall_k C_k$ exceeding the marginal value ε for a given scene SC_i $\forall_i$ are selected:

$$M_k = \{m_{ki} : \arg_i P(C_k|SC_i)P(SC_i) \geq \varepsilon\}. \tag{2}$$

A. *Definition of Relations*

Relations from a set Σ are defined according to expert knowledge.

The set Σ is a union of sets $\Sigma_1 \cup \Sigma_2 \cup \Sigma_3$, where subset Σ_1 is set of hierarchical relations (e.g. Σ_1= {is, is part of}, Σ_2 is a set of relations between class and values of its attributes (in these case elementary classes) from set D_3 (e.g. Σ_2 = {consist}) and subset Σ_3 is a set of spatial and pseudo-spatial relations defined by a spatial location of objects and by co-occurrence of objects in real scenes, respectively, like Σ_3 = {is below, is above, occurs with, occurs not with, , …}.

A. *Definition of Relations Truth Value*

For the relations from the set Σ_1 that model the class inheritance, degree of truth is set to 1 because any exceptions, if exist, can be modeled using a set of contradictions. Truth value of the relations, linking the elementary class and derived class, is defined according to the experts’ knowledge. Truth value of relation whether from the sets Σ_2 and Σ_3 is computed using data in the training set.

Truth value attached to the relation between attributes and classes was determined using discriminate function $d_i(C_k)$ defined separately for each attribute C_k. It is assumed that attributes are independent. The model is adjusted on a learning set and effectiveness of selected attributes is evaluative on the test set. Decision rule is:

$$C_k \,\epsilon\, SC_i \overset{iff}{\Leftrightarrow} j = \underset{i}{\arg\max}\, d_i(C_k), \quad \forall_i SC_i, \forall_k C_k$$
$$d_i(C_k) = \frac{P(C_k|SC_i)P(SC_i)}{\sum_{j=1}^{n} P(C_k|SC_j)P(SC_j)} \tag{3}$$

Moreover, to give greater importance to attributes with more contribution on the classification results, attribute weights are estimated by misclassification error (MCE criterion):

$$w(C_i) = 1 + \frac{1 - MCE(C_i)}{\sum_k MCE(C_k)}, \quad \forall_k C_k, \qquad 1 \leq k \leq |C|. \tag{4}$$

In Fig. 4 a part of knowledge base is presented, showing relations among particular scene class and appropriate elementary classes defined by the former procedure. For example, the degree of truth of relation between a particular class “Seaside” and its attribute, an elementary class “Water” is set to 0.95.

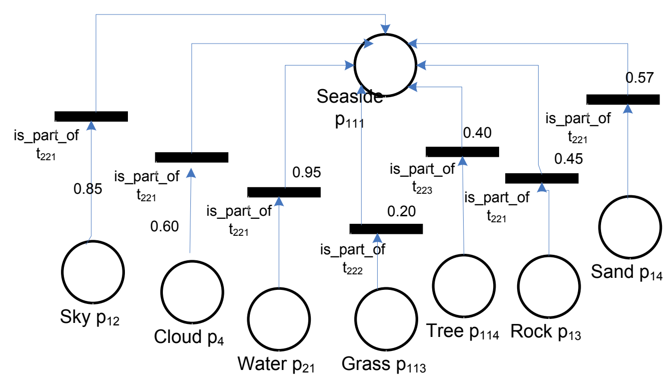

Fig. 4 Relations among scene ‘Seaside’ and appropriate elementary classes

Analyzing a mutual occurrence of classes C_j, C_i a truth value of pseudo-spatial relations can be formally defined as:

$$P(C_j|C_i) = \frac{P(C_j \cap C_i)}{P(C_i)}, \qquad i \neq j \tag{5}$$

The spatial and pseudo-spatial relationships can be used to validate and adjust the results of classification. For instance, having detected the “airplane” in the image with high probability, detection of “lion” on the same image is unlikely. Also, grass often appears under the sky, the sky above the mountains, etc.

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V. Scene Classification Using a Fuzzy Recognition Algorithm

For a task of scene classification of a new, unknown image, fuzzy recognition algorithm on inverse KRFPN scheme is used. The inverse KRFPN scheme is obtained by replacing the input and output functions of KRFPN scheme and is denoted as -KRFPN. The procedure of fuzzy recognition finds the class whose properties best match given set of attributes and relations.

Assumption is that unknown image is segmented and that low-level image features are obtained. Using some classification method as Naive Bayes, each image segment is classified in one of elementary classes according a maximum posterior probability (c_{MAP}).

The basic assumption is that attributes (feature vector components) within the class are mutually independent, so that applies:

$$P(x_1, x_2, \dots, x_n \mid C_j) \approx \prod_{j=1}^{n} P(x_i \mid C_j), \tag{6}$$

Based on the Bayes' theorem and taking into account that $P(x) = const.$ and judging $P(C_i),\ \forall C_i \in C$ on the basis of data in a learning set for each attribute value x_j of new data occurrence $\mathbf{x}^{new}$, a classification results is determined by:

$$c_{MAP} = \underset{C_i \in C}{\operatorname{argmax}} P(x^{new} \mid C_i)\, P(C_i) \tag{7}$$

The results of the classification of each segment and assessment of a posterior probability $P(C_j \mid x_i)$ are entry of the Petri net used for further classification on higher semantic level.

Thus, a set of obtained elementary classes C_i are treated as attributes of an unknown scene class X that are mapped to places $\{p_1, p_2, \dots, p_k\}$ if a function $\alpha^{-1}: C_i \rightarrow p_k$ is defined. A token value $c(m_k)$ of each place corresponds to obtain posterior probability of the appropriate elementary class C_i mapped to that place.

The initial token distribution will be a root node π_0 of the recognition tree (Fig. 5).

Fig. 5 shows corresponding recognition trees in -KRFPN scheme with enabled transition starting from the root node. Nodes of the recognition tree have a form $\left(p_j, c(m_l)\right)$ $j = 1, 2, \dots, n,\quad l = 1, 2, \dots, r,\ 0 \leq r \leq |M|$, where $c(m_l)$ is a value of token m_l in place p_j. Arcs of recognition tree are marked with value $f(t_j)$ and label of a transition $t_j \in T$ whose firing creates new nodes linked to scene classes.

The following describes the procedure for the classification of elementary classes in the scene classes using fuzzy recognition algorithm that matches the recognition trees shown in Fig. 5.

For instance, if obtained classification results are elementary classes that exist in knowledge base with corresponding degree of truth: (cloud {0.5}, rock ({0.4}), sand ({0.8}), water ({0.8}) than using function α^{-1} initially marked places are determinate (α^{-1}(cloud)=p4, α^{-1}(rock)=p13, α^{-1}(sand)=p14, α^{-1} (water)=p21). According to initially marked places and corresponding degree of truth, four recognition trees $\pi^i, i = 1,2,..4$ with root node $\pi_0{}^i, i = 1,2,..4$ will be formed (Fig. 5):

$$\pi_0^1(\emptyset,..\emptyset,\{p4,0.5\},\emptyset,\dots,\emptyset), \pi_0^2(\emptyset,..\emptyset,\{p13,0.4\},\emptyset,..\emptyset,),$$
$$\pi_0^3(\emptyset,..\emptyset,\{p14,0.8\},\emptyset,..\emptyset,), \pi_0^4(\emptyset,..\emptyset,\{p21,0.8\},\emptyset,..\emptyset,)$$

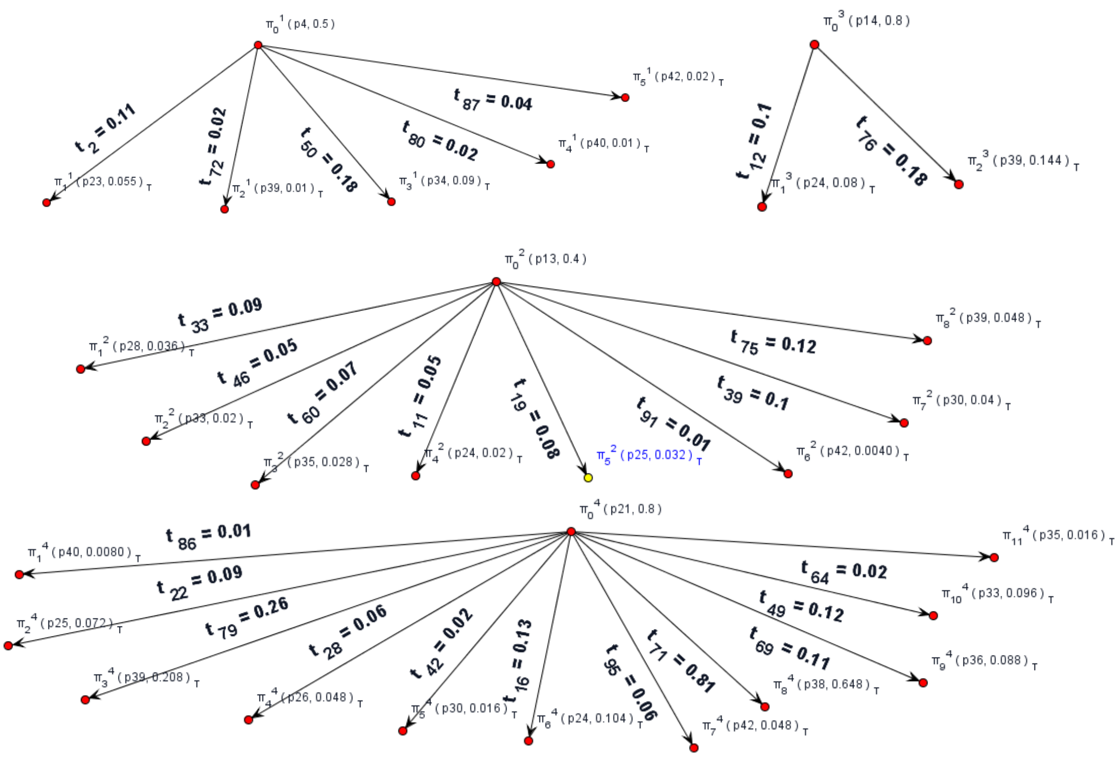

Fig 1 Recognition trees with enabled transitions for root nodes that match initially obtained elementary classes

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By firing of enabled transitions on - KRFPN scheme, new nodes on the following higher level of recognition tree are created and appropriate values of tokens are obtained:

$$c(m_{k+1}) = c(m_k) * f(t_k) = P(C_i|x) * w_i(C_i)P(C_i|SC_l)P(SC_l) \qquad (8)$$

where t_k is arc between concepts C_i and SC_l, $P(C_i|x)$ is a posterior probability of segment classification to elementary class C_i.

Accordingly, total sum of all p nodes $\pi_i{}^k, i = 1,2,..p \leq n$ $k = 1,2,..b \leq |M|$ in all b recognition trees (for this example b=4 and p=$\sum_{k=1}^{4} p^k = 5 + 8 + 2 + 11 = 28$), excluding the root node $\pi_0{}^k$, is computed as:

$$Z = \sum_{k=1}^{b} \sum_{i=1}^{p^k} \pi_i^k. \qquad (9)$$

In this example a total sum is:
$Z = \sum_{k=1}^{4} \sum_{i=1}^{p^k} \pi_i^k = \sum_{i=1}^{5} \pi_i^1 + \sum_{i=1}^{8} \pi_i^2 + \sum_{i=1}^{2} \pi_i^3 + \sum_{i=1}^{11} \pi_i^4$ = (Ø…Ø, {p23, 0.055}, {p24, 0.204}, {p25, 0.104}, {p26, 0.048}, Ø, {p28, 0.036}, Ø, {p30, 0.056}, Ø, Ø, {p33, 0.116}, {p34, 0.09}, {p35, 0.044}, {p36, 0.088}, Ø,{p38, 0.648}, {p39, 0.41}, {p40, 0.018}, Ø, {p42, 0.072}, Ø, ... Ø).

Then, a set of indices of elements with a highest sum $Z = (Z_1, Z_2, \ldots, Z_n)$ among all of the nodes in all recognition trees is selected:

$$I^* = \{i^* : \arg \max_{i=1,\ldots,n} \{Z_i\}\} \qquad (10)$$

A scene class assigned to a place with max argument $p_i : i \in I^*$ is chosen as the best match for a given set of elementary classes.

In this example, a set of max argument is $I^* = \{38\}$ and a scene class chosen as the best match for a give set of attributes is one that is assigned to place with max argument, α (p38) =‘Seaside’.
Obtained classes can be used as root nodes for next recognition process that will infer classes from higher semantic levels either because they are directly linked with the classes or may be inferred by means of classes (parents) at a higher level of hierarchy.

VI. Class Generalization Using Fuzzy Inheritance

To display the properties of the concept and its relations, fuzzy inheritance algorithm on the KRFPN scheme can be used. The fuzzy inheritance algorithm determines attributes of a classes $d_i \in D$, first locally and then at higher hierarchical levels than the classes d_i it selves. During the process of inheritance for a given $k \in \mathbb{N}$, a final tree of inheritance at the most k+1 level is constructed. As the class of interest can be at different levels of abstraction, whether at the level of the elementary class or the scene class, a key feature of inheritance algorithm is that allows the representation of knowledge at different levels of abstraction.

For a given class that exists in the database, the appropriate place is determined by the function $\alpha^{-1}(d_j) = p_k,\ d_j \in D$.

According to the initially marked place and appropriate token value, the initial token distribution is created $\Omega_0 = \pi_0 = (\emptyset, \emptyset, \ldots, \{p_k, c(m_k)\}, \ldots, \emptyset)$, which represents the root node of inheritance tree. Token value $c(m_k)$ can be set to 1 or to the value obtained by recognition algorithm.

The inheritance tree is formed by firing the enabled transitions until the condition for stopping the algorithm is satisfied or the desired depth of inheritance tree reached.

Below, a Fig. 6 shows a 1-level inheritance tree of the KRFPN scheme for one of scene classes, a "Seaside", where $\alpha^{-1}(\text{'Seaside'}) = p_{39}, c(m_1) = 1$ and the corresponding root node is $\pi_0(\emptyset,..\emptyset, \{p39, 1.0\}, \emptyset, \ldots, \emptyset)$.

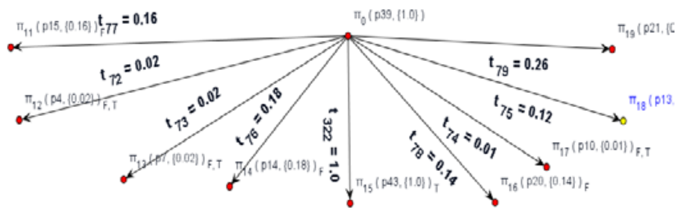

Fig. 6 The inheritance tree for a concept Seaside

Fig. 7 shows inheritance paths formed after semantic interpretation of nodes and arch displayed in Fig. 6 describing, semantically, attributes and parent classes of class “Seaside”.

Inheritance inference procedure for concept Seaside gives following conclusior

q.	Inheritance path interpretation	Associated trul
	Seaside contains cloud.	Minimally true
	Seaside contains grass.	Minimally true
	Seaside contains mountain.	Minimally true
	Seaside contains rock.	Slightly true
	Seaside contains sand.	Slightly true
	Seaside contains sky.	Slightly true
	Seaside contains trees.	Slightly true
	Seaside contains water.	Slightly true
	Seaside is Obala.	Always true

Fig. 7 Statements of inheritance for concept 'Seaside'

VII. Experimental Results

To demonstrate a model of hierarchical image classification using the KRFPN scheme, we have used a part of Corel image dataset [14].

Images were automatically segmented based on visual similarity of pixels using the Normalized Cut algorithm [16], so segments do not fully correspond to objects. Every segmented region of each image is more precisely

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characterized by a set of 16 features based on color, position, size and shape of the region [14].

Also, each image segment of interest was manually annotated with first keyword from a set of corresponding keywords provided by [16] and used as ground truth for the training model. Vocabulary used to denote the segments have 28 words related to natural and artificial objects such as 'airplane', 'bird', etc. and landscape like 'ground', 'sky', etc.

The data set used for an experiment consists of 3960 segments divided into training and testing subsets by 10-fold cross validation with 20% of observations for holdout cross-validation.

We have used the Naïve Bayes classification algorithm to classify image segment into elementary classes. The results of automatic classification of image segments are compared with ground truth, so the precision and recall measures are calculated, Fig. 8.

A recall is the ratio of correctly predicted classes and all classes for the image (ground-truth), while a precision is the ratio of correctly predicted classes, and total number of suggested classes.

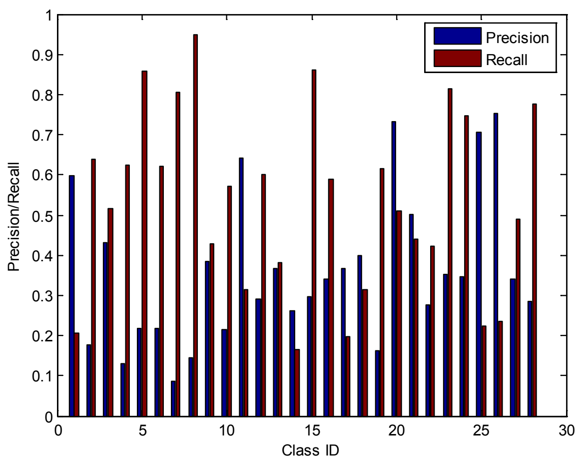

Fig. 8 A precision/recall graph for classification of image segments into elementary classes (displayed by ID)

The results of low-level image feature classification depend on the quality of segmentation, so when image has a lot of segments and when object is over segmented, the results can include labels that do not correspond to the context of image. Then, using the facts from the knowledge base, the obtained results are analyzed with the fuzzy inheritance algorithms in order to purify the classification results from class labels that do not match the contents of the image.

Afterwards, based on elementary classes obtained as classification results and knowledge developed for particular domain, an automatic image classification on higher semantic level can be performed following the fuzzy recognition algorithm. Also, the inheritance algorithm can be used to display the properties of the class and its relations with the parent classes. In Table 1 some examples of results of a multi-level image classification are indicated including results of low level image classification (the 1. row below each image) and image classification using proposed knowledge scheme (the 2. row below each image).

Table 1: Examples of scene classification

		
'train', 'tracks', 'sky'	'grass', 'tiger'	'water', 'sand', 'sky', 'road'
'Vehicle', 'Man-Made Object', 'Outdoor'	'Wildcat', 'Wildlife', 'Natural Scenes', 'Outdoor Scene'	'Coast', 'Landscape', 'Natural Scenes', 'Outdoor Scene'

VIII. Conclusion

The aim of this paper is to present a model for multi-level image classification using KRFPN formalism that uses fuzzy Petri Nets graphical notation. A precise mathematical model of Petri nets and inference algorithms, with finite recognition and inheritance inference trees, can be used to present and analyze, whether the relationships between attributes and class or between classes at a higher level of abstraction.

The complexity of the algorithm is O (nm) where n is the number of places and m number of transitions in KRFPN scheme.

A hierarchical organization of KRFPN scheme enables explanation of image classification results obtained by some other classification method, such as Naive Bayes classifier.

Furthermore, an important property of the KRFPN formalism is the ability to show the uncertain knowledge using probability or reliability of the concept and relation.

This research is limited to a domain of outdoor scenes and the knowledge base includes knowledge that is relevant to the domain. But, the methodology of acquiring knowledge and reasoning in KRFPN scheme is expandable and adaptable to the acquisition of new knowledge of a particular domain.

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