A KNOWLEDGE-BASED MULTI-LAYERED IMAGE ANNOTATION SYSTEM

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Abstract: In this paper we propose a multi-layered image-annotation system. The first layer of the image interpretation corresponds to image annotation based on the classification of image segments. The outputs of the first layer are elementary classes that correspond to objects of outdoor scenes. For higher layers of the image interpretation, in order to minimize the semantic gap, a combination of elementary classes and a knowledge-representation scheme based on the Fuzzy Petri Net (KRFPN) is used. The inference engine of the KRFPN supports the efficient inconsistency checking of the classified segments, scene recognition, as well as the inference of generalized and derived classes. The results of the image interpretation obtained for the outdoor domain (a subset of a Corel image base) were compared to the published results obtained on the same image base. Owing to the fuzzy-knowledge representation scheme, the obtained image interpretation is enriched with new, more general and abstract concepts that are close to the concepts people use to interpret these images.

1 INTRODUCTION

Digital images have become unavoidable in the professional and private lives of modern people. In recent years, the frequent use of digital images has become necessary in different fields like medicine, insurance and security systems, geo-informatics, advertising, commerce, as well as in other business areas. On the other hand, in private life, digital images are used for documenting people close to us, pets, sights and events such as birthdays, parties, trips, excursions and sporting activities. This widespread use has caused a rapid increase in the number of digital images that, today, on specialized websites, can be counted in the millions. However, a large number of images leads to problems with searching and retrieval, as well as with organizing and storing.

As the majority of images are barely documented, it is believed that we could retrieve and arrange images simply if they were automatically annotated and described with words that are used in an intuitive image search. However, the task of mapping image features that can be extracted from raw image data to words that users normally use for articulating their requirements is not a trivial one. For example, it seems natural to use a destination name when retrieving holiday images or some terms that describe a scene, such as the coast, mountains or activities like diving, skiing, etc. A major research challenge is bridging the semantic gap between the low-level image features available to a computer and the interpretation of the images in the way that humans do [Smeulders et al. 2000]. In addition, one should take into account that image interpretation inherent to humans includes concepts associated with the content of the image on different levels of abstraction. This is referred to as the multi-layered interpretation of image content.

In this paper a system for multi-layered image annotation is proposed. The first layer of the image interpretation contains concepts obtained by the classification of image segments. For higher layers a knowledge-representation scheme based on a Fuzzy Petri Net is proposed. The main contributions of our approach are associated with the use of a fuzzy knowledge-representation scheme with an integrated inference engine defined for inconsistency checking of classification results of image segments, automatic scene recognition and for deriving of classes that are more abstract. The fuzzy Petri nets are used as a graph-based image representation model. A statistical approach is used to define the facts and their truth-values in the knowledge base. The architecture of the system is general and can be adapted for new domains by acquiring new facts and adding them to the knowledge base.

The paper is organized as follows: First, in Section 2, different approaches to image-content interpretation are explained and a detailed overview of related work is given. The layers of the multi-layered image representation with respect to the amount of knowledge needed for the image interpretation are given in Section 3. A system for the multi-layered image annotation is proposed in Section 4. An example of a fuzzy-knowledge representation scheme related to the outdoor image domain is presented in Section 5. Inputs to the scheme are concepts obtained as the results of an image-segments classification using a Bayesian classifier. The application of the fuzzy inference engine for checking the consistency of the obtained results of the image segment classification and the recognition of scene context is given in Sections 6 and 7, respectively. The fuzzy inference algorithm used to derive more abstract concepts associated with the image is described in Section 8. The experimental results of the image interpretation at the layer that corresponds to automatic image annotation are given and compared to previously reported methods [Duygulu et al. 2002, Carbonetto et al. 2004] in Section 9. Additionally, in Section 9, an improvement to the results of the automatic image annotation after checking the inconsistency of the concepts obtained during the image-segments classification is presented.

2 RELATED WORK

Descriptions of various models of multi-layered image annotation are given in the literature [Shatford 1986, Eakins and Graham 2000, Hare et al. 2006]. Among the oldest is Shatford's image-content classification of general-purpose images that classifies image content as general, specific and abstract [Shatford 1986]. Additionally, the contents of an image are associated with aspects of objects, with spatial and temporal aspects and aspects of activities or events. In [Eakins and Graham 2000], a multilayer interpretation of the image content is considered in the context of image search. The authors defined three semantic layers of image interpretation. At the first level, image interpretation is based on the presence of certain combinations of features, such as color, texture or shape, while at the second level, image interpretation deals with the presence and distribution of certain types of objects. At the third level, image interpretation includes a description of specific types of events or activities, locations and emotions that one can associate with the image. The authors [Harre et al. 2006] provide a simplified hierarchical view between the two extremes, the image itself and its full semantic interpretation. At the lowest level are the image and its "raw" data. The second level consists of low-level features related to a part of an image or to the whole image. A combination of prototype feature vectors is part of the third level. If these image parts can be associated with the corresponding objects, then this would make the fourth level. The top level of image interpretation, referred to as full semantics, includes concepts that describe the events, actions, emotions and a broader context of the image.

There are two major approaches widely used for image annotation, one using statistical methods and the other mostly using knowledge-based methods belonging to the field of artificial intelligence. In the statistical approach, most methods can be grouped as translation or classification models. In the translation model of [Duygulu et al, 2002] the co-occurrence of image regions and annotation words are used to model the relationship between annotation words and images or image regions. In classification methods, such as [Barnard et al, 2003, Li and Wang, 2003, Hu and Lam, 2013], words used for image annotation correspond to class labels for which classifiers are trained. Some methods use multi-label learning for solving the problem of annotating images with more than one word [Feng and Xu, 2010].

Such statistical methods commonly use quite simple vocabularies that can be large but are generally not structured because no relations are defined between the concepts in the vocabulary. On the other hand, methods that rely on knowledge bases used sophisticated, structured vocabularies in which geometrical, hierarchical or other relations between concepts are established [Tousch et al, 2012]. This kind of vocabulary supports the multi-layered image annotation that is suitable for image retrieval.

A few approaches have explored the dependence of words on image regions [Blei and Jordan, 2003] or exploit the ontological relationships between annotation words, demonstrating their effect on automatic image annotation and retrieval [Maillot, 2005].

A comprehensive survey of research made in the field of statistical automatic image annotation methods can be found in [Liu et al, 2007, Datta et al, 2008; Zhang et al, 2012].

For a multi-layered image annotation, several approaches that use models for knowledge representation and reasoning were proposed. The authors [Benitez et al. 2000] described a semantic network to represent the semantics of multimedia content (images, video, audio, graphics and text). The basic components of the semantic network are concepts that correspond to real-world objects and the relations among them, such as generalization, aggregation and perceptual relationships based on the similarities of their low-level features.

The authors [Marques and Barman 2003] propose the model with three levels. The lowest level contains vectors of low-level features extracted from images. The feature vectors are classified into the concepts from flat vocabulary using Bayesian networks. On the highest level is the RDF ontology that contains knowledge about the keywords and information about the relations between different concepts.

The authors [Srikanth et al, 2005] proposed using a hierarchical dependency between annotation words to improve translation-based automatic image annotation and retrieval. The hierarchy is derived from the text ontology WordNet and represents the various levels of generality of the concepts expressed in image regions and words. To predict the likelihood probability of assigning a class label given an image, statistical language models defined on a visual vocabulary of blobs, represented by region feature vectors, are used.

In [Ivasic-Kos et al. 2010] a semantic image content analysis framework based on Fuzzy Petri Net is proposed for classification of image segments into objects. Also, a formal description of hierarchical and spatial relationships among concepts from the outdoor image domain is described.

In [Simou et al. 2008, Athanasiadis et al. 2009] an ontology and the inference engine FIRE (Fuzzy Inference Reasoning Engine) [Stoilos et al. 2005] were used for analyzing the image content belonging to the beach domain. Later, the same group of authors [Papadopoulos et al. 2011] compared different approaches attempting to use spatial information for semantic image analysis.

3 MULTI-LAYERED IMAGE REPRESENTATION

An image representation includes the visual content and the annotation of an image. The visual content of an image refers to the information that may be collected by analyzing low-level image features while the image annotation includes concepts that may describe both the content and the context of an image. The task of automatic image annotation is challenging because the number of possible concepts that one can use to describe most images is large, highly dependent on application, user's knowledge, needs, cultural background, etc. and it is hard to choose the right type of concepts that would be universally appropriate. For instance, to annotate the images in the Fig. 1, one can use concepts that are related to the objects that appear in the image (*sand, sea, sky, snow*), concepts that represent the scene (*beach, coast, coastline, shore, seashore*), more general scene concepts (*wildlife, outdoor, natural scene*) or activities (*walking, get wet feet*). If the user is familiar with the context of an image, its description will be more subjective and will probably include the name of a place (e.g. Tallinn, Estonia for Fig. 1a), names of the people appearing in it, description of the relevant event (e.g. Meeting for Fig. 1a) or evoked emotions, etc.

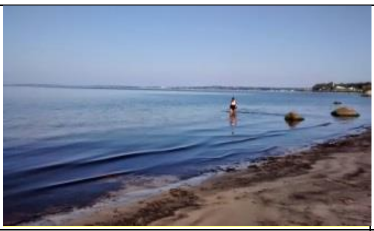
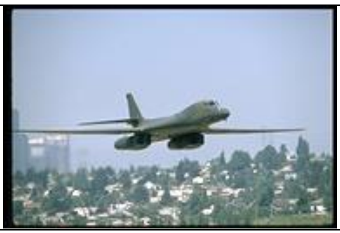
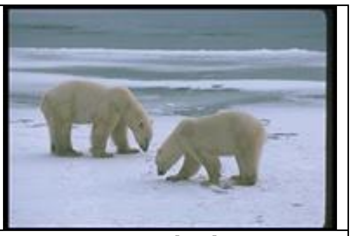
			
Objects	*sand, sea, sky*	*plane, sky, trees, building*	*snow, polar bear*
Scenes	*Coast*	*Scene Plane*	*Scene Polar bear*
More general (abstract) concepts	*Natural scene,* *Outdoor*	*Vehicle* *Man-made object,* *Outdoor*	*Wildlife,* *Mammal,* *Outdoor,* *Natural scene*
Derived concepts	*Beach, SeaShore,* *Tallinn, Estonia* *Meeting*	*Transportation*	*Arctic*

Figure 1. Examples of images and their annotation at different levels of abstraction.

Although different people will most likely use different concepts to annotate the same image, used concepts can be organized according to the amount of knowledge needed to reach each abstraction level of image interpretation [Ivasic-Kos et al, 2009]. Therefore, we propose a multi-layered image representation model in which layers correspond to concepts at different levels of abstraction. The layers reflect the increase of amount of knowledge included in the interpretation (Fig. 2) from the lower to higher layers, where the lower layers (V_1 - V_2) represent the visual content, and the layers $MI_1 - MI_4$ represent the image semantics.

The initial layer of an image representation is the layer V_0, and it represents the raw image. The image is usually segmented (layer V_1) for analysis, and the low-level features are extracted from the image segments (layer V_2). The amount of knowledge required for segmentation (layer V_1) and feature extraction (layer V_2) is low. It is assumed that a multi-layered image annotation includes concepts ranging from elementary classes EC (layer MI_1) in which image segments are classified, scene classes SC (layer MI_2) that describe the scene, ending with generalized classes GC (layer MI_3) and derived classes DC (layer MI_4). For instance, the proposed multi-layered image annotation related to Fig. 1.c) is *EC ={snow, polar bear}; SC ={Scene-Polarbear}; GC = {Wildlife, Mammal, Outdoor, Natural scene}; DC ={Arctic}.*

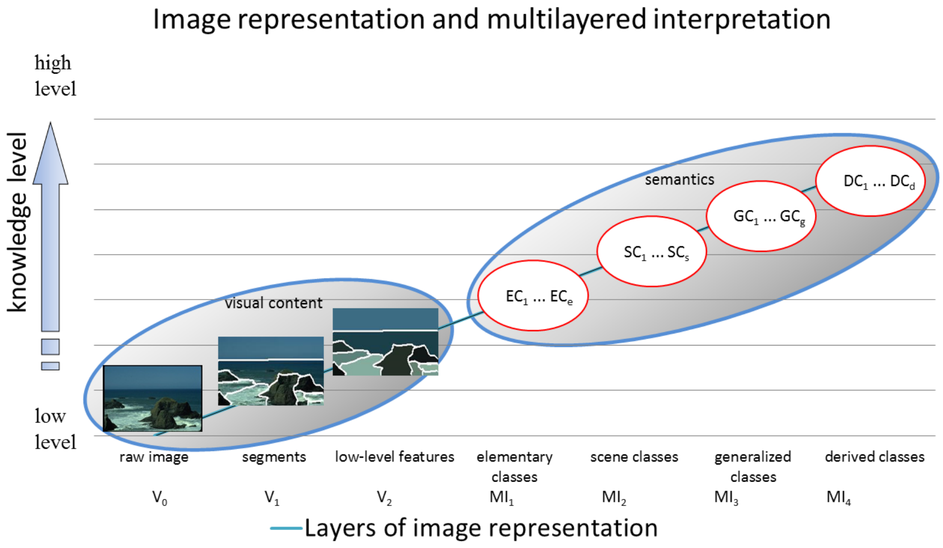


Figure 2. Layers of image representation in relation to the knowledge level

Elementary classes are obtained as the results of image-segments classification and are used as flat vocabulary for automatic image annotation. It is assumed that instances of elementary classes correspond to objects in the real world. Spatial relations, spatial locations and co-occurrence relations can be defined for elementary classes, like *EC_1 is-above EC_2*, or *EC_1 is-on-top, EC_1 occurs-with EC_3*. Scene classes are used to represent the context or semantics of the whole image, according to common sense and expert knowledge. A *part-of* relation or, its inverse, relation *consists-of*, can be defined between an elementary class and a scene class, e.g. *EC_1 is-part-of SC_2* or *SC_2 consists-of EC_1*. Generalized classes are defined as a generalization of scene classes. The *is-a* relation can be defined between a scene class and a generalized class, e.g. *SC_2 is-a GC_1*. There can be multiple levels of generalization so the relation *is-a* can be defined between generalized classes too, e.g. *GC_1 is-a GC_3 is-a GC_5*. Derived classes include abstract concepts, activities, events or emotions that can be associated with an image. Different types of relations, such as *associate-to* or *is-synonym-of* relation can be defined between derived classes and generalized or scene classes.

4 A MULTI-LAYERED IMAGE ANNOTATON SYSTEM

The architecture of our multi-layered image annotation system (MIAS) is depicted in Fig. 3. The system deals with all the layers of image representation given in Fig. 2, ranging from the segmented image at layer V_1 to the multilayer image interpretation at layer MI_4. The input to the system is an image belonging to the V_0 layer of the image representation and the system output is a multi-layered interpretation of the image that consists of concepts obtained from four layers of image interpretation, i.e., layers MI_1, MI_2, MI_3 and MI_4.

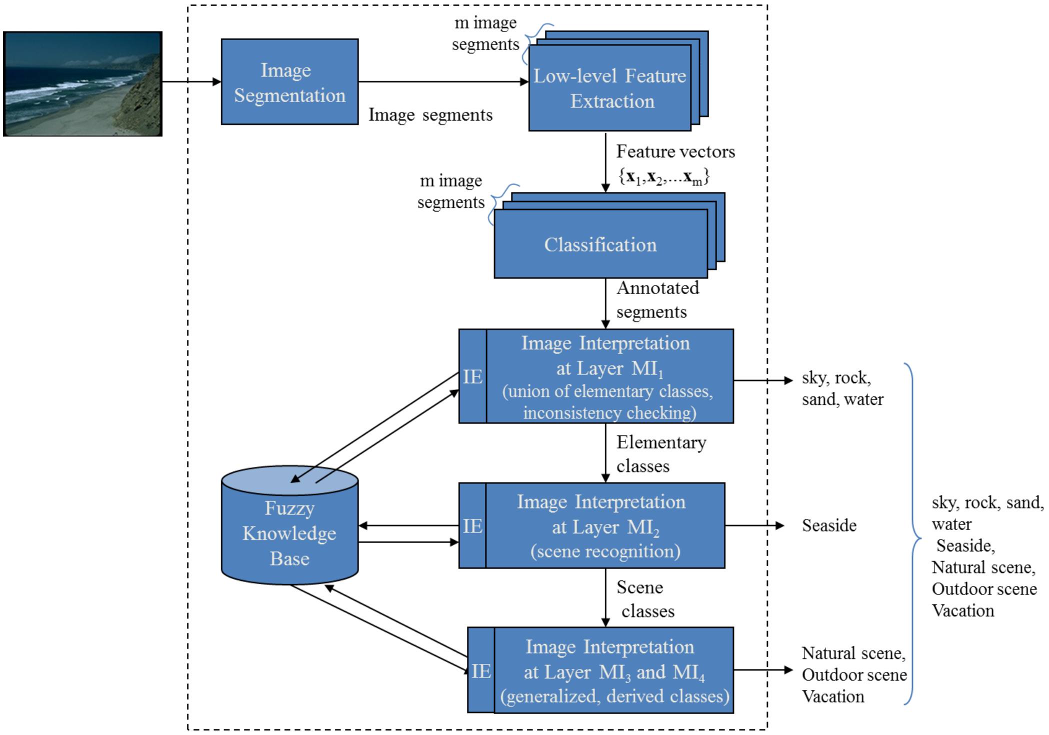

m image segments
Image Segmentation
Image segments
Low-level Feature Extraction
Feature vectors $\{\mathbf{x}_1,\mathbf{x}_2,\dots\mathbf{x}_m\}$
m image segments
Classification
Annotated segments
IE
Image Interpretation at Layer MI_1 (union of elementary classes, inconsistency checking)
sky, rock, sand, water
Elementary classes
Fuzzy Knowledge Base
IE
Image Interpretation at Layer MI_2 (scene recognition)
Seaside
Scene classes
IE
Image Interpretation at Layer MI_3 and MI_4 (generalized, derived classes)
Natural scene, Outdoor scene Vacation
sky, rock, sand, water Seaside, Natural scene, Outdoor scene Vacation

Figure 3. Architecture of a multi-layered image-interpretation system (MIAS)

A raw image I at layer V_0 is first segmented with a normalized-cuts algorithm [Shi and Malik, 2000]. The segmented image corresponds to the V_1 layer of the image representation. Formally, the relationship between the raw image I and the image segments $s_i, i = 1,..,m$ may be written as $V_1(I) = \{\mathrm{s}_1, \mathrm{s}_2, \dots, \mathrm{s}_\mathrm{m}\}$. From each image segment, low-level features are extracted (such as size, position, height, width, colour, shape, etc.) which should represent the geometric and photometric properties of a segment. Each image segment is then represented by the k-component feature vector $\boldsymbol{x} = (x_1, x_2, \dots, x_k)^T$. Accordingly, an image at the V_2 layer of the image representation is described with as many feature vectors as there are image segments. Thus, the relationship between the raw image I and the feature vectors $\boldsymbol{x}_i, i = 1,..,m$ obtained from the image segment $s_i, i = 1,..,m$ is given as $V_2(I) = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_m\}$.

Each image segment is then classified using the Bayes classifier into one of the elementary classes $EC_i \in EC$ according to the maximum posterior probability ($\mathrm{c}_{\mathrm{MAP}}$). The Bayes classifier was trained on a training set of image segments annotated with labels corresponding to natural and artificial objects. For each occurrence of the feature vector $\boldsymbol{x}$, a classification is based on the Bayes theorem:

$$c_{MAP} = \underset{EC_i \in EC}{argmax} \frac{P(\boldsymbol{x}|EC_i)\, P(EC_i)}{P(\boldsymbol{x})}. \qquad (1)$$

The conditional probability $P(\boldsymbol{x}|EC_i)$ of a feature vector $\boldsymbol{x}$ for the given elementary classes $EC_i \in EC$ and the prior probability $P(EC_i),\ \forall EC_i \in EC$ are estimated according to data in a training set. It is taken into account that the evidence factor $P(\boldsymbol{x})$ is a scale factor that does not influence the classification results.

The result of the image-segments classification is m annotated segments of the image I in such a manner that each one is annotated with one of the elementary classes. The union of elementary classes, obtained by the classification of the image segments, forms an automatic image interpretation at layer MI_1, often referred to as automatic image annotation. The classes or elements of the interpretation set $MI_1(I) \subseteq EC$ are also called labels, annotation words, or keywords.

A knowledge-representation scheme based on the Fuzzy Petri Net [Ribarić and Pavešić, 2009] is used to represent the image domain knowledge. The proposed knowledge-representation scheme has the ability to cope with uncertain, imprecise, fuzzy knowledge about concepts and relations among them.

The fuzzy knowledge base contains the following main components: fuzzy relationships between elementary classes, between elementary classes and scene classes and fuzzy relationships between scene classes and generalized or derived classes. The fuzzy relationships are defined using the training set and expert knowledge. One of the components of the system MIAS is an inference engine (IE) used for image interpretation on the layers $MI_1 - MI_4$. The inference engine supports the fuzzy inheritance and fuzzy recognition procedures. The fuzzy inheritance is used for inconsistency checking and for class generalization and the fuzzy recognition is applied for scene recognition.

The facts in the fuzzy knowledge base, particularly those related to relationships among elementary classes, are used to check the consistency of the set $MI_1(I)$. An elementary class for which it is concluded that it does not belong to a likely context, obtained e.g. due to inaccurate segmentation, can be discarded or replaced with another elementary class that has similar properties and fits the context.

The elementary classes of an image that have passed inconsistency checking are the inputs into the MI_2 image-interpretation layer for scene recognition. Each scene in the knowledge base is defined based on a training set as an aggregation of typical elementary classes. Thus, it is possible to conclude which scene is the most likely one from the elementary classes from the set $MI_1(I)$. The recognised scene class makes the image interpretation at the layer MI_2, $MI_2(I) \subseteq SC$.

Based on the scene class from the set $MI_2(I)$, more abstract generalized classes are inferred by the inference engine (see Section 5.1) using generalization relationships from the fuzzy knowledge base. Once determined, the generalized classes can be further generalized to a more abstract generalized class. Inferred generalized classes form image interpretation at the layer MI_3, so for a given image I, $MI_3(I) \subseteq GC$. The analogous inference procedure can be applied on generalized and scene classes to obtain derived classes related to a given image I, $MI_4(I) \subseteq DC$.

The outputs from the proposed system are classes at different levels of abstraction that include elementary classes, scene classes and generalized classes as well as derived classes.

5 A KNOWLEDGE-REPRESENTATION FORMALISM

To model objects and their relationships in an image, some knowledge-representation formalism has to be used and domain knowledge needs to be included. However, considering that image segmentation is often imprecise and subject to errors, and that knowledge about the concept is often incomplete, an ability to perform conclusions from imprecise, fuzzy knowledge is necessary. For this purpose, a knowledge-representation scheme based on the Fuzzy Petri Net, named KRFPN, [Ribarić and Pavešić, 2009] is adopted.

5.1 Definition of the knowledge-representation scheme adopted for the multi-layered image annotation

The elements of the knowledge base used for a multi-layered annotation of images are presented using the KRFPN scheme [Ribarić and Pavešić, 2009].

The KRFPN scheme is defined as 13-tuple: $KRFPN = (P, T, I, O, M, \Omega, \mu, f, c, \alpha, \beta, \lambda, Con)$, (2)
where the first ten components are of the marked Fuzzy Petri net (FPN) [Li and Lara-Rosano, 2000]:
$P = \{p_1, p_2, \ldots, p_n\}, n \in \mathbb{N}$ is a set of places; a function $\alpha: P \rightarrow D$ maps a place from a set P to a concept from a set D used for multi-layered image annotation. It is set that $D = EC \cup SC \cup \mathrm{GC} \cup \mathrm{DC}$ where the subset EC includes 28 elementary classes such as *{Airplane, Train, Shuttle, Ground, Cloud, Sky, Coral, Dolphin, Bird, Lion, Mountain, etc.}*, the subset SC includes 20 scene classes such as *{Seaside, Inland, Sea, Space, Airplane Scene, Train Scene, Tigre Scene, Lion Scene, etc.}*, the subset GC includes generalized classes such as *{Outdoor Scenes, Natural Scenes, Man-made Objects, Landscape, Vehicles, Wildlife, etc.}*, and subset DC includes *{Savannah, Africa, Safari, Vacation, etc.}*.

$T = \{t_1, t_2, \ldots, t_m\}, m \in \mathbb{N}$ is a set of transitions; a function $\beta: T \rightarrow \Sigma$ maps a transition from a set T to a relationship from a set Σ defined according to expert knowledge; a set Σ includes a relationship *occurs_with* between elementary classes that models the common occurrence of elementary classes in the image and its negation *not_occurs_with*, then the aggregation relationship *consists_of* defined between a scene class that has a role of aggregation and elementary classes that have the role of components of aggregation, then a generalization relationship *is_a* that is defined either between a scene class and generalized class or between generalized classes or derived classes and in addition a *is_synonim_of* relation defined between synonyms of concepts. For a relationship *consists_of* an inverse relationship *–(consists_of)=is_part_of* is defined.

$I: T \rightarrow P^{\infty}$ is an input function, while $O: T \rightarrow P^{\infty}$ is an output function for a transition. In our scheme, the co-domain of input and output functions is a set P instead of a bag P^{∞} as defined in [Peterson, 1981].

$M = \{m_1, m_2, \ldots, m_r\}, 1 \leq r < \infty$ is a set of tokens used by the inference engine. The inference procedure is based on the dynamic properties of the Petri Net, i.e. by firing of the transitions [Peterson, 1981]. The tokens' distribution within places is given as $\Omega(\mathrm{p}) \in \mathcal{P}(M)$, where $\mathcal{P}(M)$ is a power set of M. The initial distribution of tokens defines the initial marking vector $\boldsymbol{\mu}_0 = (\mu_1, \mu_2, \ldots, \mu_n)$ and $\mu_i = \mu(p_i) \in \{0, 1\}$, i.e. in the initial marking a place can have no or at most one token. In case of scene recognition, $\boldsymbol{\mu}_0$ corresponds to elementary classes obtained at the layer MI_1.

$c: M \rightarrow [0, 1]$ is an association function that gives a token value that corresponds to the degree of truth of the concept mapped to a place marked with that token. The value of a token in an initial distribution can be set to the estimated posteriori probability of a concept that is associated with that marked place or set to 1.

$f: T \rightarrow [0, 1]$ is an association function that gives a transition value that corresponds to the degree of truth of a relationship mapped to a transition. The measure of truthfulness of the relationship depends on the relationship kind and is computed using data in the training set in case of pseudo-spatial and spatial relationships based on co-occurrence of elementary classes in images. Also the function f can be defined by an expert in case of more abstract classes (*SC*, *GC* and *DC*).

$\lambda \in [0, 1]$ is a threshold value related to transitions firing. If the threshold value λ is set, the truth value $\mathrm{c(m_1)}$ of each token must exceed the value of λ if the transition is to be enabled.

$Con \subseteq (\Sigma \times \Sigma)$ is in this scheme defined as a set of pairs of mutually contradictory relations. It is defined on a set of relations $occurs\_with$, not_occurs_with between elementary classes. It can be also defined between concepts if necessary.

The KRFPN scheme can be represented by a directed graph containing two types of nodes: places and transitions. Graphically, the places $p_i \in P$ are represented by circles and the transitions $t_j \in T$ by bars. The directed arcs between the places and transitions, and the transitions and places represent the transition input $I(t_j) \subseteq P$ and output $O(t_j) \subseteq P$ functions, respectively (Fig. 4). In a semantic sense, each place from the set P corresponds to a concept $d_i \in D$ and any transition from set T to a relation $r_k \in \Sigma$.

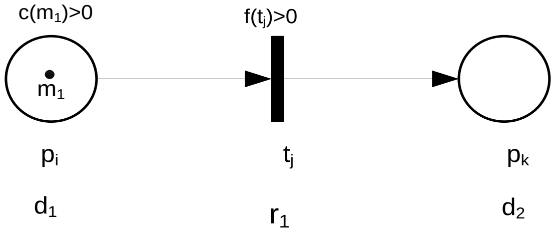


Figure 4. A generic form of a chunk of knowledge in the Fuzzy Petri Net formalism

A dot within a place represents a token $m_1 \in M$. To a token at the input place $p_i \in I(t_j)$ and the transition $t_j \in T$, the values $c(m_1)$ and $f(t_j)$ are assigned, respectively. The assigned values implement uncertainty and fuzziness in the scheme and can be expressed by truth scales, where 0 means “not true” and 1 “always true”. Semantically, a value $c(m_1)$ expresses the degree of uncertainty of a concept $d_i \in D$ mapped to a particular place $p_i \in P$, and the value $f(t_j)$ corresponds to the degree of uncertainty of a relationship $r_i \in \Sigma$ mapped to a transition $t_j \in T$.

A place that contains one or more tokens is called a marked place. The tokens give dynamic properties to the Petri Net and define its execution by firing an enabled transition. A transition is enabled when every input place of the transition is marked, i.e., if each of the input places of the transition has at least one token and if each token value exceeds the threshold value λ.

An enabled transition t_j can be fired. By firing, a token moves from all its input places $p_i \in I(t_j)$ to the corresponding output places $p_k \in O(t_j)$. In Fig. 4, there is only one input place for the transition t_j, $I(t_j) = p_i$ and only one output place $O(t_j) = p_k$. After the transition firing, a new token value $c(m_2)$ at the output place is obtained as $c(m_1)f\left(t_j\right)$ (Fig. 5).

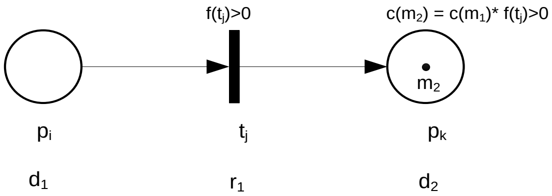


Figure 5. A new token value is obtained in the output place after firing.

The dynamic properties of the scheme are important for the inference-engine definition. The inference engine on the KRFPN scheme consists of three automated reasoning processes: fuzzy inheritance, fuzzy recognition and fuzzy intersection. All the steps of the inference algorithms are given in [Ribarić and Pavešić, 2009], and below is a brief description of their application for inconsistency checking, scene recognition and for generalized and derived class inference.

5.2 Modelling the truth value of relationships

Given that the mapping between concepts and image features is often unreliable, and due to incomplete knowledge of the concepts, the uncertainty is implemented into the scheme by associating a value with a transition and with a token in a marked place. A transition value expresses the degree of truth or the reliability of the related relationship, while a token value corresponds to the truth value or the reliability of the concept. The degree of truth of the relationships depends on the type of the relationship and is set according to the expert knowledge or it is computed using data in the training set. For example, the degrees of truth of the relationships that model the generalization of classes are determined by the expert, while the truth value of the relationships $consists\_of$ and $occurs\_with$ is computed using data in the training set, as explained below.

5.2.1. Relationship *consists_of*

To define the truth value of the aggregation relationships $consists\_of$ it is assumed that a scene may contain several characteristic elementary classes, so the relation among the scene and elementary classes is an aggregation relationship where the scene plays the role of the aggregation and the elementary classes have the role of the components of the aggregation. Analyzing the data in the training set, a common occurrence of elementary classes in the scene class is determined. Instead of choosing an elementary class with a maximum posterior probability, the modified Bayes rule is used to form a set MS that corresponds to the specific scene class. A set MS_{SC_i} for a specific scene class $SC_i\ \forall_i$ is given by:

$$MS_{SC_i} = \{EC_k : \underset{i}{arg}\, P(SC_i|EC_k) \approx \underset{k}{arg} \frac{P(EC_k|SC_i)}{P(EC_k)} \geq \varepsilon\}. \qquad (3)$$

The eq. (3) mirrors the idea of finding a most representative set of elementary classes for a given scene class. MS_{SC_i} is a set of all those elementary classes $EC_k, k = 1,2, \dots$ that participate in a scene class SC_i with the posterior probability $P(SC_i|EC_k), \forall_k\, EC_k$ exceeding the marginal value ε ≥ 0.05. The marginal value is determined experimentally. The prior probability $P(EC_k)$ for a given elementary class EC_k is obtained from the training set and it brings in the degree of discrimination of each elementary class for a given scene class.

The truth value attached to the aggregation relationship $consists\_of$ between the elementary classes and the scene class was determined using the Bayes rule for the posterior probability $P(SC_i|EC_k), \forall_k\, EC_k \in MS_{SC_i}$ for the specific scene:

$$P(SC_i|EC_k) = \frac{P(EC_k|SC_i)P(SC_i)}{\sum_{j=1}^{s} P(EC_k|SC_j)P(SC_j)}, \qquad (4)$$

$s = |SC|$ is a number of scene classes.

In Fig. 6, a part of a knowledge base is presented, showing the relationships among a particular scene class *seaside* and its components that correspond to elementary classes from the set $MS_{seaside} = \{sky, cloud, water, grass, tree, rock, sand, building\}$ defined by the eq. (3). The degree of truth $f(t_j)$ of the transition t_j that corresponds to the relation *consists_of* between a particular scene class "*Seaside*" and its components, is given by *P(Seaside*|EC_k*)*, $EC_k \in MS_{seaside}$ and is determined by eq. (4). For instance, truth value of relation *consists_of* mapped to transition t_{86} between a scene class "*Seaside*" of place p_{45} and elementary class "*water*" of place p26 is $f(t_{86}) = 0.95$.

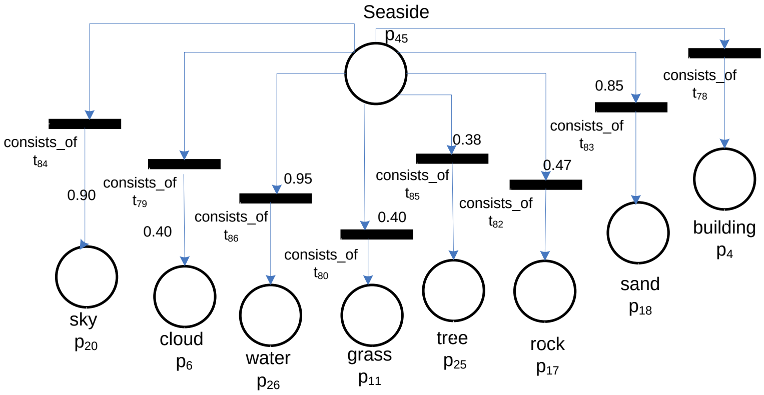


Figure 6. Relations among the scene "*Seaside*" and its components

5.2.2. Relationship *occurs_with*

To define the truth value of the relationship $occurs\_with$, a mutual occurrence of classes EC_j and EC_i in the training set is analyzed. This can be formally defined as:

$$P(EC_j|EC_i) = \frac{P(EC_j \cap EC_i)}{P(EC_i)}. \qquad (5)$$

If the $P(EC_j|EC_i)$ is less than the threshold value τ = 0.1 then the relationship *not_occurs_with* is defined between elementary classes EC_j and EC_i, $i \neq j$ with the truth value of 0.9. Otherwise, the truth value of the *not_occurs_with* relationship is $1 - P(EC_j|EC_i)$. The *occurs_with* relationship is used to validate the results of the image segment classification and to check whether the results obtained on all the image segments are consistent.

5.2.2. Spatial relationships

Spatial relationships like *at the top*, *at the bottom*, have not been used in this experiment since the relationships between the objects in the image differed from the natural relations. In images from the domain of natural scenes that we have used, the sky, trees, grass and water can appear both at the bottom and at the top of the image, so for example, water can appear above the grass and trees, as in Fig. 7 e). Ellipses in the Fig 7. a) - e) show the positions of the segments that are not in line with the common knowledge about spatial relationships of objects in nature. For example, the grass segment in Fig. 7 c) is above the tiger segment.

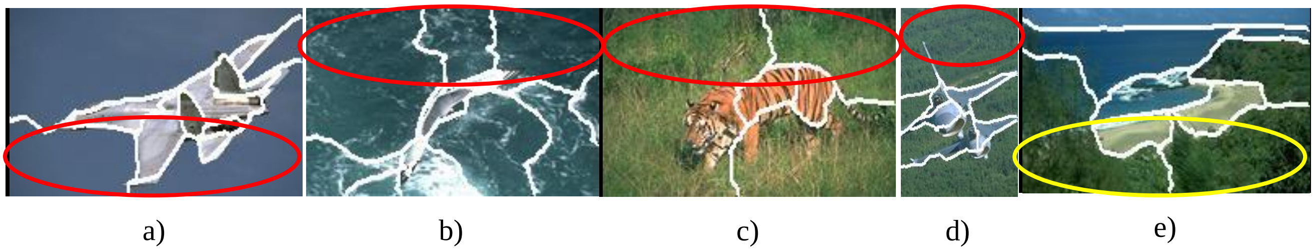


Figure 7. Position of objects sky, water, grass, trees and the spatial relations between the objects in the image

If it turns out to be useful, spatial relationships, as well as fuzzy temporal relationships or new concepts can be added to the scheme.

6 KOWLEDGE-BASED APPROACH TO INCONSISTENCY CHECKING

It is to be expected that some of the elementary classes obtained using the Bayes classification rule (Eq. 4) do not fit the image context. To check for inconsistency of the obtained elementary classes, the facts included in the knowledge base related to the *occurs_with* and *not_occurs_with* relations are used. The relations *occurs_with* and *not_occurs_with* for each obtained elementary class can be analyzed using the fuzzy-inheritance algorithm, explained in detail in [Ribarić and Pavešić, 2009]. Based on the results of fuzzy inheritance, the classes which are elements of domain of relation *not_occurs_with* are eliminated from the set MI_1, the first semantic layer.

In order to illustrate the fuzzy inheritance procedure, an example follows. Let the image I in Fig. 8 be given for a multi-layered image annotation. After the segmentation, using a normalized-cuts algorithm, the image is segmented into 7 areas: $V_1(I) = \{s_1, s_2, \ldots, s_7\}$. For each image segment the low-level features are extracted and a feature vector is formed, so the image is represented at level V_2 by the set of feature vectors: $V_2(I) = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_7\}$. Then, using the Bayes classification method, each feature vector is classified into one of the elementary classes $EC_i \epsilon$ EC according to the maximum posterior probability (c_{MAP}, Eq. (1)). For image I in Fig. 8, the obtained result, after the classification of all the image segments, is: "$sky, water, water, shuttle, rock, water, sand$". Thus, the set of obtained elementary classes forms an automatic image interpretation at the layer MI_1 of the image I, as $MI_1(I) = \{sky, water, shuttle, rock, sand\}$. Note that the elementary class *shuttle* is a result of misclassification, because a shuttle is not present in the image.

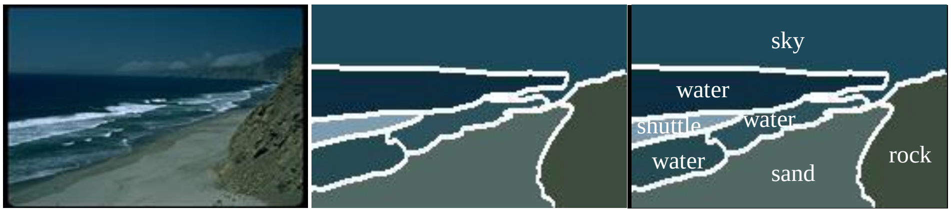


Figure 8. Example of image representations at layers V_0, V_1, MI_1

Every obtained elementary class can be checked for inconsistency using the not_occurs_with relationships defined between elementary classes in $MI_1(I)$ and the fuzzy-inheritance algorithm.

For instance, to check the inconsistency of the elementary class *shuttle*, the fuzzy-inheritance algorithm is used as follows. The appropriate place in the knowledge-representation scheme is determined by the function $\alpha^{-1}(shuttle) = p_{19}$, $shuttle \in EC$ (Fig. 9). On the Fig. 9, presented are those *not_occurs_with* relations for which *shuttle* is the input place. The initial token distribution is $\Omega_0 = (\emptyset, \emptyset, \dots., \{p_{19}, 1\}, \dots, \emptyset)$, i.e. the initial token is placed only on the place p_{19}. For inconsistency checking only relations with outputs from the set $MI_1(I)$ are useful and are shown in black. According to the original FPN algorithm all transitions related to these relations are enabled and can be fired because the number of tokens in the input place (*shuttle*) is equal to the number of input arcs of the transitions. The transition values are obtained from the training set using Eq. (5). After firing, the token is removed from the input place (*shuttle*) and new tokens are created and distributed to output places (*sand, rock, water*, …) as shown in Fig. 9b.

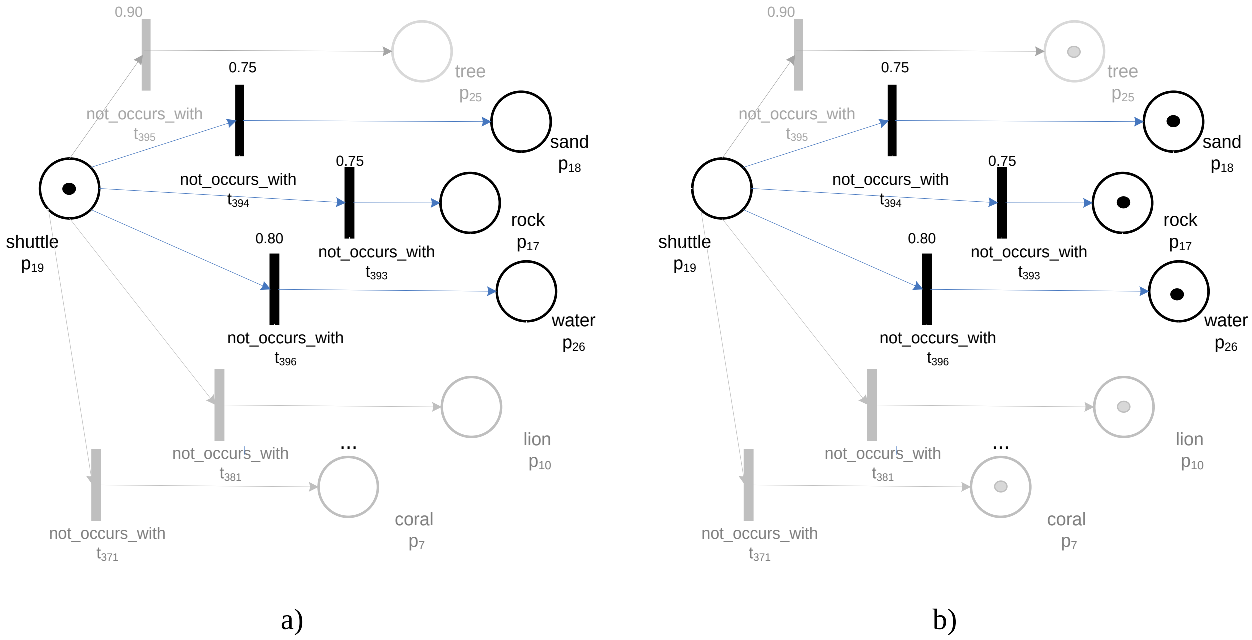
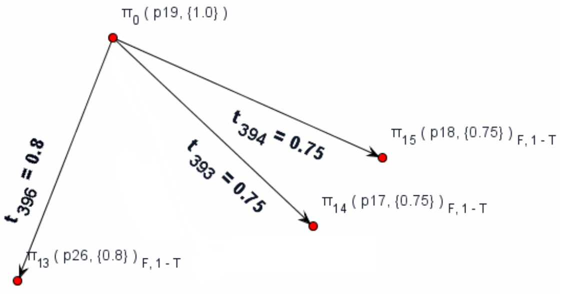


Figure 9. A part of KRFPN scheme related to elementary class *shuttle* and the relationship *not_occurs_with* a) before firing and b) after firing the transitions.

The inheritance tree is formed starting from the root node which is for this example $\pi_0(p_{19}, \{1.0\})$. Firing of the transitions creates new frontier nodes of the inheritance tree that correspond to output places of transitions. This step is repeated until the condition for stopping of the algorithm is satisfied or the desired depth of the inheritance tree is reached. The frontier nodes are converted by the inheritance tree algorithm into the frozen node (marked F), k-terminal (marked k-T) or identical (marked I), or one of the types of nodes defined for the reachability tree (terminal, duplicate and interior). The inheritance tree of the KRFPN is similar to the concept of reachability tree of Petri Nets [Chen et al. 1990], except for the stopping conditions that are integrated in the KRFPN scheme (by the set $\Sigma \backslash \{is\_a\}$) or defined by the desired number of tree levels. Fig. 10 shows a 1-level inheritance tree on the KRFPN scheme and the appropriate semantic interpretation of the inheritance paths for the elementary class *shuttle*. The nodes of the inheritance tree have the form $\left(p_j, c(m_l)\right)$ $j = 1,2,\ldots,p,$ $l= 1,2,\ldots,r,$ $0 \le r \le |M|,$ where $c(m_l)$ is the value of a token m_l in place p_j, computed as the product of the token value at the input place and the corresponding value $f(t_j)$. The arcs of the inheritance tree are marked with a value $f(t_j)$ and the label of a transition $t_j \in T$, where, for example, $t_{396} = 0.8$ means $f(t_{396}) = 0.8$. For each of the inheritance paths the measure of truth is determined by the token value in a leaf node (the node in which the algorithm stops).



π_0 (p19, {1.0})
$t_{394} = 0.75$
$t_{393} = 0.75$
$t_{396} = 0.8$
π_{15} (p18, {0.75}) F, 1 - T
π_{14} (p17, {0.75}) F, 1 - T
π_{13} (p26, {0.8}) F, 1 - T

Figure 10. Inheritance tree for the class *"shuttle"* (Fig.9)

The obtained inheritance tree for the concept *shuttle* gives the conclusion that the class *shuttle* does not occur with the elementary classes from the set $MI_1(I)$, so it can be concluded that the class *shuttle* most likely does not match the context of the image depicted in Fig. 8 and therefore can be discarded.

Accordingly, after checking for the inconsistency, the refined image interpretation at the semantic layer MI_1 is: $MI_1(I) = \{sky, rock, sand, water\}$.

7 SCENE RECOGNITION

For the task of scene recognition for a new, unknown image, the fuzzy-recognition algorithm based on the inverse KRFPN scheme (marked as –KRFPN) is used [Ribarić and Pavešić, 2009]. The –KRFPN scheme is obtained by interchanging the position of the input I and the output O functions for the transition T in the 13-tuple. Additionally, by changing the position of the input and output functions, the relation mapped to the transition is transformed into its corresponding inverse relation. For example, for the relation *consists_of* in the KRFPN scheme its inverse relation *is_part_of* is used in the –KRFPN scheme, i.e., –*(consists_of)=is_part_of*. Also, the co-domain of the associated function $c: M \to [0,1]$ that assigns values to the tokens (see 5.1) is expanded by $c_r: M \to [-1, 1]$ so that in the case of an exception, a token may be associated with a negative value.

The procedure for the scene recognition is as follows. The results of the image interpretation at layer MI_1, after inconsistency checking, are the input to the scheme used for further image interpretation at the layer MI_2. The obtained elementary classes EC_i from $MI_1(I)$ are treated as components of an unknown scene class X.

The elementary classes EC_i are mapped to the places $\{p_1, p_2, \dots, p_n\}$ using the function $\alpha^{-1}: EC_i \to p_k$. If defined, the reliability based on a posterior probability of each elementary class EC_i can be used as the token value $c_r(m_l)$ in the place p_k, whose interpretations correspond to the given class EC_i. Otherwise, a token value is set to 1.

For instance, let us take an image I depicted in Fig. 8. The results of the image interpretation at the layer $MI_1(I)$ are elementary classes $\{sky, rock, sand, water\}$ that exist in the knowledge base. Based on the Bayes classification rule (eq. 1) the degrees of truth are assigned: (sky {0.5}, sand ({0.7}), rock ({0.4}), water ({0.6}). By using the function α^{-1} the initially marked places are determined (α^{-1}*(sky) =* p_{20}, α^{-1}*(sand) =* p_{18}, α^{-1}*(rock) =* p_{17}, α^{-1}*(water) =* p_{26}). A small part of a –KRFPN scheme with initially marked places and the corresponding token value is given in Fig. 11.

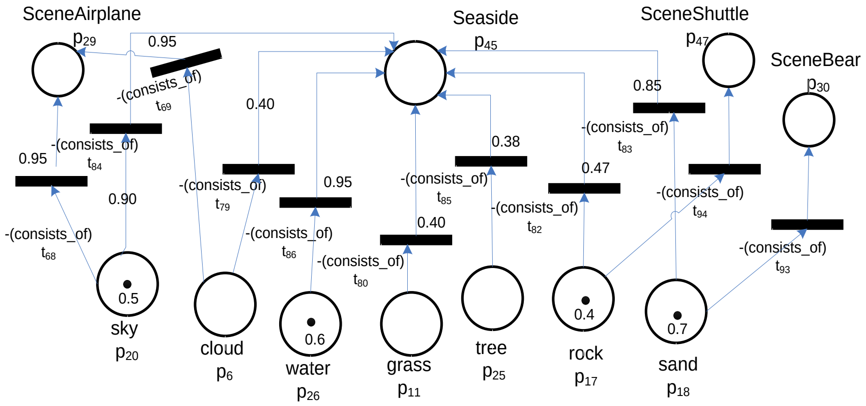


Figure 11. A small part of the –KRFPN scheme for the scene recognition for image depicted in Fig.8.

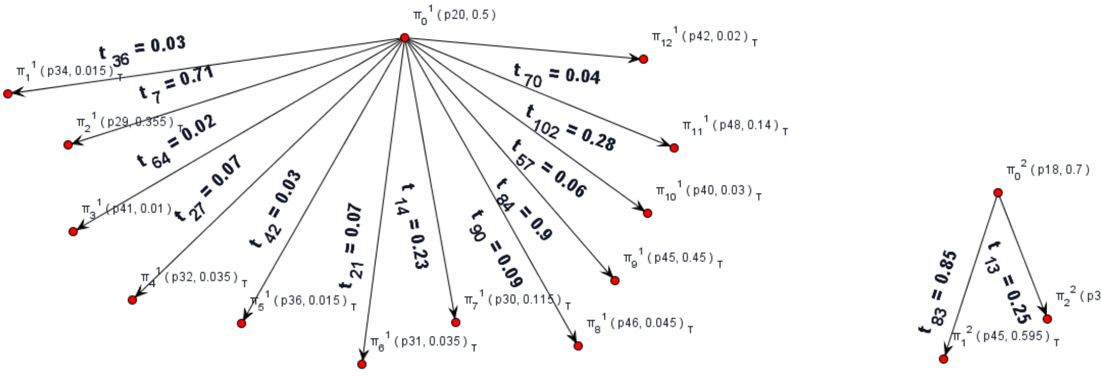
According to the initially marked places and the corresponding degrees of truth, four root nodes $\pi_0{}^{\mathrm{i}}, \mathrm{i} = 1, \ldots, 4$ of the recognition trees will be formed:

$$\pi_0^1(\mathrm{p}_{20}, \{0.5\}), \pi_0^2(\mathrm{p}_{18}, \{0.7\}), \pi_0^3(\mathrm{p}_{17}, \{0.4\}), \pi_0^4(\mathrm{p}_{26}, \{0.6\}).$$

Fig. 12 shows four corresponding recognition trees in the -KRFPN scheme with enabled transitions, starting from the root node. By firing of the enabled transitions on the -KRFPN scheme, new nodes at the following higher level of the recognition tree are created and appropriate values of the tokens are obtained:

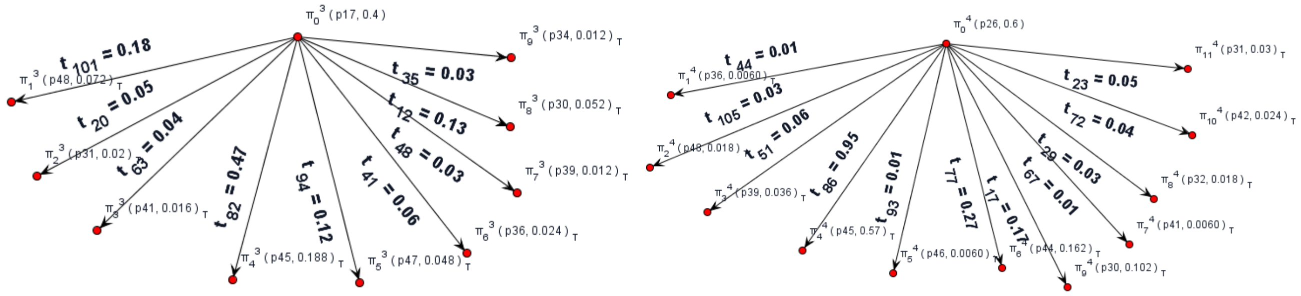
$$c_r(m_{k+1}) = c_r(m_k) f(t_l) \qquad (6)$$

where t_l is the transition between concepts EC_i and SC_l, $c_r(m_k)$ is the reliability of the elementary class EC_i and $f(t_l)$ is computed in eq (4). Due to the simplicity of the example, only one level of the recognition tree is generated. Note that only the recognition tree with the root node π_0^2 (Fig. 12.b)) directly corresponds to the small part of –KRFPN depicted in Fig. 11. The other recognition trees (Fig. 12.a), c) and d)) also contain leaf nodes corresponding to the scene classes that are part of the knowledge base but are not depicted in Fig. 11.



a)

b)


π$_0^3$ (p17, 0.4)
t$_{101}$ = 0.18
π$_1^3$ (p48, 0.072)$_T$
t$_{20}$ = 0.05
π$_2^3$ (p31, 0.02)$_T$
t$_{63}$ = 0.04
π$_3^3$ (p41, 0.016)$_T$
t$_{82}$ = 0.47
π$_4^3$ (p45, 0.188)$_T$
t$_{94}$ = 0.12
π$_5^3$ (p47, 0.048)$_T$
t$_{41}$ = 0.06
π$_6^3$ (p36, 0.024)$_T$
t$_{48}$ = 0.03
π$_7^3$ (p39, 0.012)$_T$
t$_{12}$ = 0.13
π$_8^3$ (p30, 0.052)$_T$
t$_{35}$ = 0.03
π$_9^3$ (p34, 0.012)$_T$
π$_0^4$ (p26, 0.6)
t$_{44}$ = 0.01
π$_1^4$ (p36, 0.0060)$_T$
t$_{105}$ = 0.03
π$_2^4$ (p48, 0.018)$_T$
t$_{51}$ = 0.06
π$_3^4$ (p39, 0.036)$_T$
t$_{86}$ = 0.95
π$_4^4$ (p45, 0.57)$_T$
t$_{93}$ = 0.01
π$_5^4$ (p46, 0.0060)$_T$
t$_{77}$ = 0.27
π$_6^4$ (p44, 0.162)$_T$
t$_{17}$ = 0.17
π$_9^4$ (p30, 0.102)$_T$
t$_{67}$ = 0.01
π$_7^4$ (p41, 0.0060)$_T$
t$_{29}$ = 0.03
π$_8^4$ (p32, 0.018)$_T$
t$_{72}$ = 0.04
π$_{10}^4$ (p42, 0.024)$_T$
t$_{23}$ = 0.05
π$_{11}^4$ (p31, 0.03)$_T$

c) d)

Figure 12. Recognition trees with enabled transitions for each root node

The following steps of scene recognition are as follows. Each leaf node $\pi_{\mathrm{i}}{}^{\mathrm{k}}$ in the recognition tree $k = 1, 2, \ldots, b$ is represented by a vector of dimension |P|, where P is a set of places, so the index of a node in the recognition tree corresponds to the index of the vector component and the value of a node is assigned to a value of the vector component. For example, a node $\pi_1{}^2 = (\mathrm{p}_{45}, 0.595)$ (Fig. 12b)) is represented by the vector $\boldsymbol{\pi}_1{}^2 = (0, 0 \ldots 0, 0.595, 0, \ldots, 0)$ so that all the vector components are assented to a value 0, except the 45th vector component, to which a node value of 0.595 is assigned. Accordingly, the total sum $\boldsymbol{Z}$ of all leaf nodes in all recognition trees is computed:

$$\boldsymbol{Z} = \sum_{k=1}^{b} \sum_{i=1}^{o^k} \boldsymbol{\pi}_i^k. \qquad (7)$$

where $\boldsymbol{\pi}_i{}^k$ is i-th leaf node in the k–th recognition tree, $b \leq |M|$ is the number of recognition trees, $o^k \leq |P|$ is the total number of leaves in the recognition tree k.

In this example there is $b = 4$ recognition trees, the corresponding numbers of leaves are: $o^1 = 12, o^2 = 2, o^3 = 9, o^4 = 11$, and the total sum is:

$\boldsymbol{Z} = \sum_{k=1}^{4} \sum_{i=1}^{o^k} \boldsymbol{\pi}_i^k = \sum_{i=1}^{12} \boldsymbol{\pi}_i^1 + \sum_{i=1}^{2} \boldsymbol{\pi}_i^2 + \sum_{i=1}^{9} \boldsymbol{\pi}_i^3 + \sum_{i=1}^{11} \boldsymbol{\pi}_i^4$ = (0…0, 0.36, 0.44, 0.09, 0.05, 0, 0.03, 0, 0.04, 0, 0, 0.05, 0.03, 0.03, 0.04, 0, 0.16, 1.80, 0.05, 0.05, 1.11, 0, ...0).

For example, the 30th component of the vector $\boldsymbol{Z}$ with the value 0.44 is obtained by summing all the values of the nodes in all the recognition trees that correspond to the place p_{30} (i.e. $\pi_7^1, \pi_2^2, \pi_8^3, \pi_9^4$): $0.115 + 0.175 + 0.052 + 0.102 = 0.44$

Then, a set of indices of elements with the highest sum $\boldsymbol{Z} = (Z_1, Z_2, \ldots, Z_{|P|})$ among all of the nodes in all the recognition trees is selected as:

$$i^* = arg \max_{i\, =\, 1,\ldots,|P|} \{Z_i\}. \qquad (8)$$

In the case that there are several i for which the same maximum value of $\{Z_i\}$ is obtained, the set I^* is created:

$$I^* = \{i_1^*, i_2^*, \ldots\}. \qquad (9)$$

A scene class assigned to a place with the max argument p_i: $i \in I^*$ is chosen as the best match for a given set of elementary classes obtained during image interpretation at the layer MI_1. In this example, the 45th component of the vector Z has the maximum value 1.80. Therefore, a set of max arguments consists of only one element $i_1^* = 45$, so only one scene class is chosen as the best match, i.e., the one that is assigned to a place with that max argument, $\alpha\,(p45) = Seaside$. The next scene candidate is $\alpha\,(p48) = Inland$ with a value of 1.11.

By merging all the classes that are so far associated with the image, from elementary classes to the scene class, the multi-layered interpretation of the image is formed. For example, a multi-layered interpretation of image I (in Fig. 8) includes the results of the image interpretation at the layers MI_1 and MI_2: $MI(I) = MI_1(I) \cup MI_2(I) = \{sky, rock, sand, water\} \cup \{ Seaside\}$.

8 INFERENCE OF MORE ABSTRACT CLASSES

The obtained scene classes can be used as root nodes for the next inheritance process that will infer more abstract concepts from higher semantic levels (here referred as generalized and derived classes) either because they are directly linked with the concept or may be inferred by means of concepts at a higher level of abstraction (parents).

To determine related, more abstract classes for a given scene class, the relations with its parents at higher levels of abstraction are inspected using an inheritance algorithm [Ribarić, Pavešić, 2009]. The procedure by which more abstract classes are inference will be illustrated using the example of scene class $Seaside \in SC$ that was obtained as a result of the recognition algorithm in Section 7. In Fig. 13, a part of a knowledge base is shown that includes information about the components of the class "*Seaside*" and its more abstract classes defined by expert.

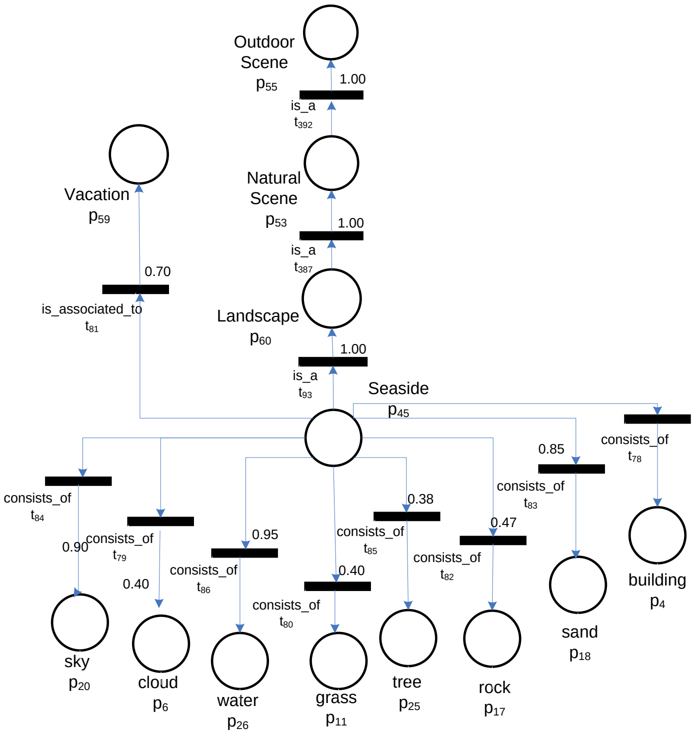


Figure 13. A part of the knowledge base that shows the properties of the class *"Seaside"* and its parents

At the first step of the algorithm the appropriate place is determined by the function $\alpha^{-1}(Seaside) = p_{45}$. A token value $c(m_l)$ is set to 1, so the corresponding root node of the inheritance tree is $\pi_0(p_{45}, \{1.0\})$. Fig. 14 shows a 3-level inheritance tree on the KRFPN scheme for the class '*Seaside*' that shows its more abstract classes (nodes within the ellipsis) as well as its properties.

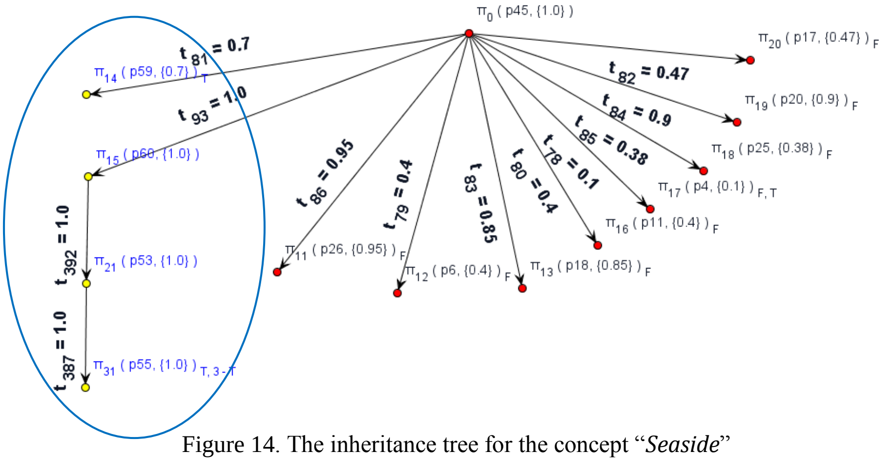


Figure 14. The inheritance tree for the concept "*Seaside*"

To determine more abstract classes associated with the given class, the key nodes are those in the parent-child relationship with the given class and statements formed along that arc. The nodes in parent-child relationship for the class '*Seaside*' are: $\pi_{14}(p_{59}, \{0.7\})$, $\pi_{15}(p_{60}, \{1.0\})$, $\pi_{21}(p_{53}, \{1.0\})$ and $\pi_{31}(p_{55}, \{1.0\})$ and the following applies: $\alpha(p_{59}) = Vacation$, $\alpha(p_{60}) = Landscape$, $\alpha(p_{53}) = Natural\ scene$, $\alpha(p_{55}) = Outdoor\ scene$. The classes "*Landscape*", "*Natural scene*" and "*Outdoor scene*" are a generalization of the class "*Seaside*", while the class "*Vacation*" is a derived class that one can associate with the class "*Seaside*" using the relation *is_associated_to*.

Thus, the result of a multi-layered image annotation for the image *I* given in Fig. 8, after the generalization and the derived-concepts inference is:

$$MI(I) = MI_1(I) \cup MI_2(I) \cup MI_3(I) \cup MI_4(I) =$$
$$\{sky, rock, sand, water\} \cup \{Seaside\} \cup \{Landscape, Natural\ scene, Outdoor\ scene\} \cup \{\ Vacation\}.$$

Also, new concepts can be added to the knowledge. Some examples of such an extension are synonyms of the concepts defined in a scheme like *Seacoast* for *Seaside* or terms that are colloquially understood as synonyms like *Forest* or *Logs* for *Trees*. In these cases, the *is_synonim_of* relation is defined between a class that is already defined in the knowledge base (e.g. *Seaside*) and the synonym that should be added (e.g., *Seacoast)*. Fig. 15 shows the fuzzy-inheritance tree for the concept *Seacoast*, for which applies $\alpha^{-1}(Seacoast) = p_{57}$, so the corresponding root node of the inheritance tree is $\pi_0(p_{57}, \{1.0\})$.

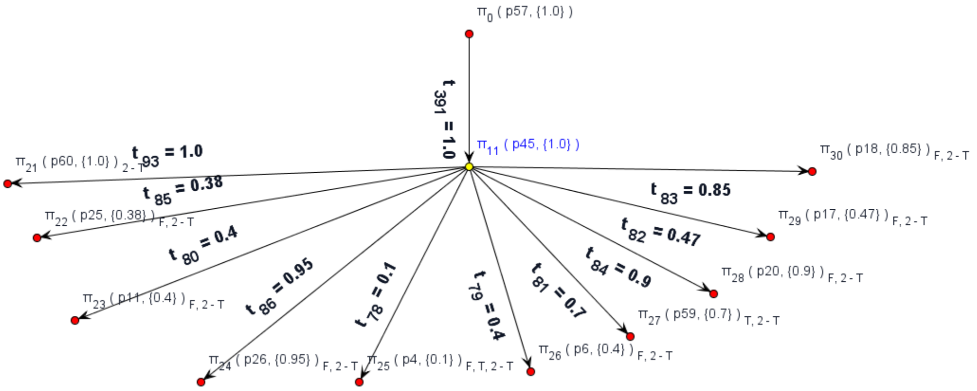

π0 (p57, {1.0})
t391 = 1.0
π11 (p45, {1.0})
π21 (p60, {1.0}) 2 - T
t93 = 1.0
t85 = 0.38
π22 (p25, {0.38}) F, 2 - T
t80 = 0.4
π23 (p11, {0.4}) F, 2 - T
t86 = 0.95
π24 (p26, {0.95}) F, 2 - T
t78 = 0.1
π25 (p4, {0.1}) F, T, 2 - T
t79 = 0.4
π26 (p6, {0.4}) F, 2 - T
t81 = 0.7
π27 (p59, {0.7}) T, 2 - T
t84 = 0.9
π28 (p20, {0.9}) F, 2 - T
t82 = 0.47
π29 (p17, {0.47}) F, 2 - T
t83 = 0.85
π30 (p18, {0.85}) F, 2 - T

Figure 15. The inheritance tree for a synonym of *Seacoast* concept *Seaside*

Inclusion of concepts at different levels of abstraction maps the organization of concepts from natural language to image annotation and facilitates the adjustment of the system to the user's needs and expectations.

9 EXPERIMENTAL RESULTS

To evaluate the proposed model of a multi-layered image annotation a part of the Corel image dataset related to outdoor scenes (e.g., Landscape, Vehicles, Animals, Space) [Carbonetto et al, 2004] was used.

The images were automatically segmented, based on the visual similarity of the pixels, using the normalized-cut algorithm. Every image segment was more precisely characterized by a set of 16 features based on the color in CIE L*a*b* color model, size, position, height, width and shape of the area [Duygulu et al, 2002].

The data set used for the experiment consists of 3960 segments obtained from 475 images of the outdoors. The most of images were segmented into approximately 10 regions. The data was divided into training (3160) and testing (800) subsets by a 10-fold holdout cross validation.

Also, each image segment of interest was manually annotated with the first keyword from the set of corresponding keywords provided by [Carbonetto et al, 2004] and used as the ground truth for the training model. The vocabulary used to denote the image segments has 28 keywords related to natural and artificial objects such as 'airplane', 'bird', 'lion', 'train' etc. and landscape like 'ground', 'sky', 'water' etc. The keywords from the vocabulary correspond to the elementary classes.

The results of the image classification of our MIAS system at layer MI_1 are compared with the ground truth and the precision and recall measures are shown in Fig. 16.

The recall is the ratio of correctly predicted elementary classes (*tp* - true positive) and all elementary classes in the ground-truth data (*tp* + *fn*; *fn* - false negative):

$$Recall = \frac{tp}{tp + fn}. \qquad (10)$$

The precision is the ratio of correctly predicted elementary classes (*tp*) and total number of elementary classes obtained from the automatic image interpretation at layer MI_1 of the MIAS (*tp* + *fp*; *fp* - false positive):

$$Precision = \frac{tp}{tp + fp} \qquad (11)$$

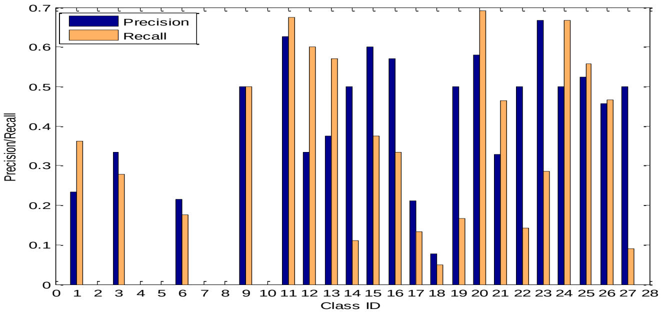


Figure 16. A precision/recall graph for the image automatic interpretation with MIAS at layer MI_1

The proposed system MIAS for image interpretation at the layer MI_1 achieves an average precision of 32.6% and average recall of 27.5%. The average precision is calculated as the average of all the values of precision that are obtained for each elementary class in the test set using the 10-fold cross validation. Similarly, the average recall is calculated as the average of all the values of recall that are obtained for each elementary class in the test set. Each elementary class in the graph (Fig. 16) is marked with class ID, so that ID 1 corresponds to the elementary class 'airplane', ID 2 to the elementary class 'bear', ID 3 to elementary class 'bird' and so on until ID 28 that corresponds to elementary class 'zebra'. The highest precision, over 56% was obtained for the elementary classes: ‘grass’- ID 11, ‘polar bear’ - ID 15, ‘rock’ - ID 16, ‘sky’ - ID 20 and ‘tracks’ - ID 23. The highest recall, over 57% was obtained for the elementary classes: ‘grass’ - ID 11, ‘ground’ - ID 12, ‘rock’ - ID 13, ‘sky’ - ID 20, ‘train’ - ID 24 and ‘trees’ - ID 25. For elementary classes ‘bear’ – ID 2, 'building' – ID 4, 'cheetah' – ID 5, 'coral' – ID 7, 'dolphin' – ID 8, 'fox' – ID 10 and 'zebra' – ID 28 obtained value for both, precision and recall, is zero. Some of the reasons for this outcome are too few samples that we had available for the particular elementary class (e.g. for the class building we had only 24 segments, for the class dolphin only 20 segments), then the big diversity of features within the class (e.g. instances of class coral significantly differ in color) as well as errors in segmentation.

The obtained result, given as outputs of MIAS at layer MI_1, is compared to the results of the models published in [Carbonetto et al. 2004]. The results of the automatic image annotation obtained for the mentioned set of images with the dMRF model defined in [Carbonetto et al. 2004] and the dInd model from [Duygulu et al. 2002] are published in [Carbonetto et al. 2004]. The dMRF model uses the method of Markov random fields for the automatic image annotation, while the dInd model is an example of a translation model that treats image annotation as the translation between two discrete languages. The authors have reported the precision for the task of automatic image annotation for each of 28 keywords in the vocabulary achieved by both models. Comparing the results of the automatic annotation on images related to outdoor scenes, the dMRF model achieves an average precision of 21%, while the dInd model achieves an average precision of 20%. As specified in the Table 1, average precision of MIAS at layer MI_1 exceeds the precision of both models although our system has correctly predicted fewer classes, 21 classes out of 28 possible.

Table 1. Comparison of the results achieved with MIAS at MI_1, dInd, dMRF

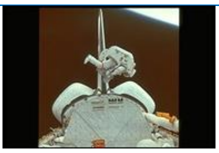
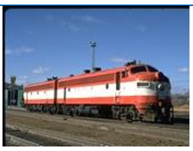
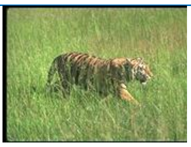
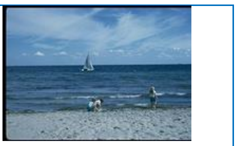
Models	*MIAS – MI₁*	*dInd*	*dMRF*
Number of correctly predicted classes	21	23	24
Average precision	32.6%	19.9%	21%

Comparing the results presented in Table 1, it should be noted that, for learning, the models dInd and dMRF used image labels, while our approach uses labels of the image segments. Because of the supervised learning approach, somewhat better results were expected. However, the achieved difference for the average precision is significant, although the dMRF model took into account the context. Note that the given results of our system MIAS at layer MI_1 (represented in Table 1.) are without any checking for inconsistency.

Generally, the results achieved by image automatic annotation models on outdoor image domains are relatively poor and the question is whether they can meet customer requirements when retrieving or organizing images. Often, the results of automatic annotation depend on the quality of the segmentation, so when an image has a lot of segments and when an object is over segmented, the results can include labels that do not correspond to the context of an image. Here, by using the facts from the knowledge base and the relationships between elementary classes, the obtained results of the image interpretation at the layer MI_1 are analyzed with fuzzy inheritance algorithms in order to purify the classification results from class labels that do not match the likely context of the image. Using inconsistency checking, those elementary classes that are obtained as a result of the image interpretation at layer $MI_1$and did not fit the likely context are discarded. As a consequence, the precision of the image interpretation at layer MI_1 is increased up to 43%. A further improvement of the precision could be achieved by defining additional relationships between the elementary classes.

Afterwards, automatic image interpretation at layer MI_2 of the MIAS is performed by the fuzzy-recognition algorithm, using elementary classes obtained as the results of image interpretation at layer MI_1 and knowledge about a particular domain. Obtained precision of automatic image interpretation at layer MI_2 is 61% and the recall is 55%. The results at the layer MI_2 depend on the results at layer MI_1. For those scenes for which there is one main object class which is highly discriminant for that scene (e.g *train* for *SceneTrain)*, it is crucial to detect that object. In this kind of scenes background objects that are common to most scenes do not play an important role, but in scenes without one prominent object (e.g. *Sea*, *Inland*) they are important. Additionally, the inheritance algorithm is used to infer generalized classes related to a scene class that make the interpretation at the layer MI_3 and derived classes at the layer MI_4. In Table 2, some examples of a multi-layered image annotation obtained by MIAS are shown.

Table 2. Examples of multi-layered image annotation by MIAS

Image example:					
Multi-layered image annotation	MI_1	'shuttle' - ID 19	'train' – ID 24, 'tracks '– ID 23, 'sky' - ID 20	'grass' – ID 11, 'tiger'- ID 22	'water' – ID 26, 'sand' – ID 18, 'sky' - ID 20, 'road'- ID 16
	MI_2	'Shuttle Scene',	'Train Scene',	'Tiger Scene',	'Seaside',
	MI_3	'Vehicle', 'Man-Made Object', 'Outdoor'	'Vehicle', 'Man-Made Object', 'Outdoor'	'Wildcat', 'Wildlife', 'Natural Scenes', 'Outdoor Scene'	'Natural Scenes', 'Outdoor Scene'
	MI_4	'Space'	'Transport'	'Savannah'	'Vacation'

10 CONCLUSION

The aim of this paper is to present the knowledge based multi-layered image annotation system MIAS. In order to bridge the semantic gap between visual content of an image and its semantics, the MIAS deals with visual content (low level features) and semantic (elementary, scene, generalized and derived classes) image representation layers.

The semantic layers are inspired by human image interpretation. The first semantic layer of the image annotation contains concepts obtained from the classification of the image segments. For higher layers that require a larger amount of knowledge, a fuzzy knowledge-base and a fuzzy inference engine are used. A hierarchical organization of the knowledge base facilitates its compatibility with various classification methods, so that a Bayesian classifier is used for the image-segments classification.

The fuzzy knowledge base is built using a knowledge representation scheme based on Fuzzy Petri Nets (KRFPN). The facts in the knowledge base are defined using data in the learning set. The facts from the knowledge base are visualized by bipartite directed graphs. The fuzzy inference engine supports inheritance and recognition inference procedures. The inheritance procedure at the level MI_1 is used for inconsistency checking of the classification results of image segments, and for inferring more abstract classes such as generalized and derived classes. The recognition procedure is used for scene recognition at the MI_2 level. The complexity of both inference procedures is $O(nm)$, where n is the number of places (concepts) and m is the number of transitions (relations) in the knowledge base.

In case of image annotation, it is important to be able to handle the uncertainty of the image-segments classification and the incompleteness of knowledge.

The ability of the MIAS to draw conclusions from imprecise, fuzzy knowledge turned out to be an important property.

Comparing the obtained results of the image annotation at layer MI_1 of the MIAS with the published results of automatic image annotations [Duygulu et al. 2002, Carbonetto et al. 2004], on the same set of images as well as using the same image features, it has been shown that the supervised learning approach provides significantly better results than the unsupervised methods used in [Duygulu et al. 2002, Carbonetto et al. 2004], even when they take into account the context [Carbonetto et al. 2004].

Furthermore, the result obtained with our approach at layer MI_1, which includes inconsistency checking, considering the knowledge facts, significantly improves the average precision. Additionally, the proposed system supports the recognition of scenes and conclusions about the related concepts at different levels of abstraction.

This research is oriented to the domain of outdoor images, so the knowledge base includes knowledge that is relevant to that domain. It should be mentioned that the proposed architecture of the MIAS system is general and can be used for different domains by extending and adapting the fuzzy knowledge base.

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