Hierarchical Heterogeneous Knowledge-base Model
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Abstract - This paper presents a hierarchical heterogeneous knowledge-base model. The model is designed to support manipulation with human knowledge about real or abstract concepts from the real world that are uncertain, ambiguous, vague and fuzzy. It has two levels: a lower associative and a higher semantic. It enables processing of novel concepts in the inheritance and the recognition inference processes at the semantic level. Novel concepts at the semantic level are substituted with “similar” concepts that are retrieved from the associative level. By using this approach it is possible to resolve novel concept’s “meaning”. The approach of this work was inspired by biological, neurological and psychological models obtained by analyzing how animal and human brains abstract, process and store knowledge from the interaction with the environment.

I. INTRODUCTION

The goal of this paper is to present a hierarchical heterogeneous knowledge-base model able to replicate a possible way how a human mind handles unknown concepts by making analogies to that which are known. The model is designed to support manipulation with human knowledge about real or abstract concepts from the real world that are uncertain, ambiguous, vague and fuzzy. The approach of this work was inspired by biological, neurological and psychological models obtained by analyzing how animal and human brains abstract, process and store knowledge from the interaction with the environment [1-13].

For example, the biological visual system reveals a hierarchical organization of neurons and their axonal projections. An activation of a particular subset of visual retinal receptors will necessarily cause neural activity at peripheral levels being summed and integrated by neurons at more central or higher levels [1-4]. Note that the studies of the visual system are given as an example because of its complexity, but same concepts of a hierarchical and a heterogeneous organization can be found for hearing, smell, taste, motor, cognitive and other activities [3,7].

The studies [1-13] describe how the hierarchical and the heterogeneous brain organization results with differences in the processing of known stimuli in contrast to unknown. In early studies of the visual system [1, 2, 4], based on information obtained by microelectrodes that were placed in the brain, it was shown that when a particular level in the hierarchy was activated by a known stimulus it wasn’t necessary for neurons at lower levels in the hierarchy to be activated in order to activate neurons at the apex of the hierarchy. Familiar stimuli are quickly recognized and they travel fast from the lowest to the top level with minimal number of neurons activations at each level. But if stimulus is novel at one level then neurons activated at that level activate large number of neurons at preceding level. This process activates similar known stimuli that are connected in the experience, based on the maximum overlap of subsets of neurons that encode known and unknown stimuli.

Hierarchical processing of stimuli in the brain is mediated by forward connections that connect lower to higher hierarchical levels and backward connections that connect higher to lower levels [5]. Important anatomical and functional distinctions between forward and backward connections are [5]: forward connections are less divergent, and transmit known stimuli directly to higher levels, backward connections are more divergent and they are used when processing unknown stimuli. Because the brain can’t process unknown stimuli they have to be substituted with the most similar known already learned stimuli. Backward connections are used to obtain similar stimuli to unknown stimuli by activating large areas of a lower level in the hierarchy. Similar stimuli obtained in such a way from a lower level, with maximal overlap, by means of forward connections again activate higher level in the hierarchy. Note that the forward and the backward connections can be used both simultaneously and recursively for multiple cycles [5]. This can explain why familiar faces are recognized in milliseconds due to dominant use of forward connections but some faces from distant past can take minutes to be recognized due to dominant use of backward connections recursively in many cycles.

Concepts from the real world that are learned through interaction with the environment can be represented as stimuli and are encoded in the brain with activations of corresponding subsets of neurons. Similarities between incoming stimuli and those that encode concepts from the real world are estimated in the brain based on the number of overlapping subsets of corresponding neurons. Minimum overlap required to recognize incoming stimulus as a known, already learned, concept is not known but it has to be significantly larger than a random one. This mechanism ensures that a particular known object will always be recognized as the same object irrespective of its orientation or size. Also note that the principle of similarity reasoning can be attributed to an inborn tendency to group elements of perception so that stimuli connected in the experience will become similar because they activate overlapping subsets of neurons. Incoming stimuli are processed starting from the lowest to the top level where abstraction increases with each higher level and number of unique real or abstract facts decreases [4]. When visual stimuli activate the top level in the hierarchy of the visual system then they are interpreted as real or abstract facts from the real world. The hierarchical information processing in the brain
helps to support robust reasoning. The brain possesses unparallel ability to process novel stimuli based on similarities to already known concepts. Even when minimal similarity is present, the brain is sometimes still able to make assumptions based on the intuition.

An example of the hierarchical and heterogeneous organization of the brain can be found in the organization of levels of the visual system. Levels are located at different brain regions which are hierarchically connected. Levels are heterogeneous because size, shape and internal organization of neurons are dependent on the particular tasks that are performed at each level [1-3]. Immediate perception is mediated by the specific sensory systems, located in the primary cortical receiving areas [6]. Episodic memory and associative learning are mediated by activation of the thalamocortical circuits formed by point-to-point connections between neurons of the non-specific thalamic nuclei and neurons in the cortical “association” areas. It is important to highlight that non-specific thalamocortical circuits are sensitive to stimulation from more than one sensory modality [6]. Furthermore, the brain’s region called the cortical “associative” area connects sensory modalities like eyes, hearing, smell, and taste to brain’s region dedicated to higher level of abstraction containing semantic description of the real world [6].

In [5] two fundamental principles of functional organization of the brain, namely functional integration and functional specialization are described. The integration within and among specialized areas is mediated by neuron connectivity and is very complex. Forward and backward connections between levels are described. Lateral connections that connect regions within a hierarchical level are depicted.

To conclude biological support for selecting a hierarchical and heterogeneous design of the knowledge-base proposed in this paper, the neuroanatomical study [7] is quoted: “All the cortical systems we studied displayed a significant degree of hierarchical organization”. They have also shown that the visual and somato-motor systems have the organizations that are “surprisingly strictly hierarchical”.

On the other side, the psychological support for a hierarchical and heterogeneous multilevel organization of the knowledge-base can be found in study by Piaget and Inhelder [8] who have studied the intellectual development of children. Their observations confirm that the acquisition of knowledge about specific objects starts at lower, and proceeds to higher levels of abstraction. Integration and differentiation is observed so that knowledge entails a more complete and detailed representation of individual things within more complex framework of relationships between the different objects of experience [8]. Hierarchical learning systems have been demonstrated by the phenomena discovered and studied by the Gestalt psychology [9, 10]. From psychological studies [8-10] follows that hierarchical organization helps to promote the integration of information related to particular object and the differentiation of this information from that associated with other objects. Psychologist in [6] suppose that hierarchical organization of the visual system is key modality by which we can look at few lines drawn on a sheet of paper and immediately recognize some well known person. In addition to providing a mechanism for the integration of information, hierarchical organization is also used to keep the elements of perception separate. Only high levels of hierarchy in the visual system are able to recognize pain in somebody’s face.

Based on the biological, neurological and psychological data [1-13] the hierarchical heterogeneous knowledge-base model in this paper was designed with two-levels: the associative and the semantic level. The associative level is selected to be the lower level based on the neurological data [6], previously mentioned, that indicate that non-specific thalamocortical circuits (in the cortical “association” areas) are sensitive to stimulation from more than one sensory modality. With assumption that sensory modalities like eyes, hearing, smell, and taste are the lowest level it follows that the associative level is the immediate higher level. The associative level is implemented with the associative memory model of the Kanerva-like Sparse Distributed Memory (SDM) [14]. The semantic level is the immediate higher to the associative level in the hierarchy because “associative” area in the brain connects lower sensory modalities to the higher semantic level [6]. Neurological data presented in [11] indicate a key role of the semantic memory to the cognitive performance. Semantic memory in the brain contains knowledge that represents common facts and the meanings of concepts [11]. It is often referred to as a conscious recollection of factual information and general knowledge in the brain from the real world. Semantic memory impairments in humans can result with difficulties in recognizing or naming specific categories of objects [12]. For example, some patients can name artefacts but have difficulty with animals, whereas others can name animals with more competence than artefacts [12]. It can also result with impairments in perceptual synthesis, phonological or lexico-semantic analysis that is specific for certain categories of stimuli [13]. The neuroimaging evidence in [13] indicates that left hippocampal areas show an increase in activity during semantic memory tasks, especially in two regions in the right middle frontal gyrus and the area of the right inferior temporal gyrus. The semantic level is implemented by the Knowledge Representation Scheme (KRS) based on the Fuzzy Petri Net theory (FPN) called KRFPN [15]. The KRFPN is used to model human’s knowledge about facts from the real world that is very often uncertain, ambiguous, vague and fuzzy.

Model of the hierarchical heterogeneous knowledge-base presented in this paper is able to replicate discussed biological, neurological and psychological findings so that some of the results from these studies naturally translate to parameters of the model. Brief overview is as follows: the hierarchical heterogeneous brain organization is replicated, if concepts are unknown at one level then the system tries to substitute them with known (already learned) similar concepts retrieved from a lower level of the system, degree of overlap of subsets of neurons corresponds to the similarity measure at the associative level, processing time of unknown concepts relative to known takes much longer, the associative level is lower compared with the semantic level.

By using two-level hierarchical heterogeneous knowledge-base design it is possible to integrate different kinds of knowledge representation schemes at every level thus making design heterogeneous. With minimalist approach the model was created with minimal number of levels and sufficient representational capacity to support mentioned biological, neurological and psychological studies. It is designed to replicate a possible way how human mind handles novel input.
sensory modalities. It enables efficient and robust human-like information storage, retrieval and inference.

II. RELATED WORK

In [16] a heterogeneous hierarchical knowledge-base model called HETHI is described. It consists of one level of the Kanerva-like SDM that performs the associative retrieval information process and supports the initialization of the inheritance process at higher levels – the semantic and rule-based levels. HETHI supports different reasoning procedures: “pure” associative inference which is performed only by means of first associative level, inference procedure defined at semantic level and inference procedure based on the cooperation of the associative and the semantic level. The HETHI was starting point for the system presented in this paper. Used algorithms are significantly redesigned and improved [33, 34]. At the semantic level a new knowledge representation scheme capable to support manipulation with human knowledge about real or abstract facts from the real world that is uncertain, ambiguous, vague and fuzzy is used.

In [17], an enhanced version of the SDM, augmented with the use of genetic algorithms, as an associative memory in a ‘conscious’ software agent CMattie is described. CMattie, as an intelligent agent, interacts with seminar organizers via email in natural language and is responsible for emailing seminar announcements in an academic department. The SDM is used as a key ingredient in the complex agent architecture that implements global workspace theory, a psychological theory of consciousness and cognition. In this architecture, the SDM, as the primary memory for the agent, provides associations with incoming precepts. The agent relies on SDM for its internal decisions on what to do next; based on the incoming percept. Two main types of memory are used in CMattie, SDM as a long term associative memory and a case based memory (CBM) as an episodic memory.

In [18] the authors describe in detail the IDA (Intelligent Distribution Agent) architecture of autonomous software agents as a cognitive model of human cognition that employs the SDM as a working, episodic and associative memory. The IDA heterogeneous, hierarchical architecture is composed of a number of different levels (10 levels), each devoted to a particular cognitive process: perception, working memory, emotions associative memory, episodic memory, consciousness, action selection, constraint satisfaction, deliberation voluntary action, language integration, metacognition. An example of a system based on the IDA, used for gathering logistical and medical information from a patient for later use by the triage nurse, is given in [19].

In [20] a general framework for learning perception-based navigational behaviours in autonomous mobile robots is presented. A multi level hierarchical behaviour-based decomposition of the control architecture is used. Lower level reactive behaviours such as collision detection and obstacle avoidance are learned by using a stochastic hill-climbing method while higher level goal-directed navigation is achieved using a sparse distributed memory. The robot is used to navigate from arbitrary locations to a desired goal location.

In [21] the SDM is used for multilevel cognitive tasks. The SDM memory is organized to link low-level information and high-level correlations. The authors conducted experiments that combined the pattern recognition of individual English characters followed by the assignment of ‘meaning’ to a string by giving it a Hebrew translation.

In [22] the effects of similarity on associative recognition are studied. Psychological experiments whether participants are more likely to give positive responses in associative recognition when a test pair consists of related words (synonyms, antonyms, or members of the same taxonomic category) than when it consists of unrelated words. The conclusion is that similarity between words enhances associative memory recall rate and may reflect the fact that related pairs are higher-frequency units than are unrelated pairs. However, a test on item recognition, in which items were studied individually but tested a pair at a time, led to fewer positive responses to related pairs than to unrelated pairs.

In [23] issues in developing cognitive architectures as generic computational models of cognition are discussed in detail. This paper presents a set of essential desiderata for developing cognitive architectures. It argues for the importance of taking full consideration these desiderata in developing future architectures that are more cognitively and ecologically realistic. A two level hierarchical heterogeneous design as most appropriate following listed criteria is proposed. An architecture CLARION satisfying these criteria is described. It consists of two levels: the top level that captures explicit processes and the bottom level that handles implicit processes. The CLARION provides a conceptual reasoning capability.

In [24] a knowledge-based model for heterogeneous multi-robot system that can be regarded as a primitive prototype of a future symbiotic autonomous human-robot system is presented. With using frame-based knowledge representation, a knowledge model is constructed to describe the features of heterogeneous robots as well as their behaviours according to human requests. The proposed system integrates heterogeneous robots and various techniques for robots, and also can automatically perform human-robot interaction, (such as speech, image recognition) and plan robot behaviours taking into account different intelligence of robots corresponding to human requests. An actual heterogeneous multi-robot system comprised of humanoid robots (Robovie, PINO), mobile robot (Scout) and entertainment robot dog (AIBO) is built and the effectiveness of the proposed system is tested by an experiment.

In [25] psychological judgments of associative memory (JAM) were presented by ratings given to pairs of cue and response words. The normed probabilities, p(response|cue), were obtained from free association norms. The JAM function was generalized across materials presented with method of rating. The function was not affected by expectancies or semantic similarity. A computer simulation model (MINERVA 2) successfully accounted for complex phenomena (like the joint influence of forward and backward associative strengths on ratings).

In [26] applications of artificial intelligence technologies are described in biomedical software and equipment. This paper describes the Think! formalism: a unified symbolic-connectionist representation scheme able to integrate different knowledge representation schemes in a single model thus enabling the use of existing knowledge bases and existing knowledge extraction techniques to make them communicate and work together. The model is based on three structure
elements: containers, processes and tubes. The structure elements define a network representing the knowledge-base. Reasoning is achieved by propagating excitations through the network from one element to another and by making calculations on these excitations. Excitations, the basic data of the network, are a pair consisting of a numerical value and an associated truth value.

In [26] cooperation of heterogeneous Information Systems is discussed. Cooperation of heterogeneous information systems requires advanced architectures able to solve conflicts coming from data heterogeneity. The project ACSIS (Agents for Cooperation of Secure Information Systems) presents a way to resolve semantic conflicts coming from databases heterogeneity. A multi-level architecture is proposed for the cooperation of heterogeneous information systems. This solution enables semantic conflict resolution by using agents and ontology.

III. HIERARCHICAL HETEROGENEOUS KNOWLEDGE-BASE MODEL

In this Section the system design will be presented. Brief overview and description of two levels will be given. Fig. 1 shows the associative and the semantic level of the hierarchical heterogeneous knowledge-base system. Main entities for storage, retrieval and inference processes at both levels of the system are real or abstract concepts from the real world. Concepts stored at the associative level are denoted with C and at the semantic level with D. Note that D ⊆ C and that the number of concepts stored at the associative level is much larger than at the semantic level, i.e. Card(C) >> Card(D), where Card denotes a cardinality of a set.

![Fig. 1. The levels of the hierarchical heterogeneous knowledge-base system.](image)

A. Associative level

Main task of the associative level is to support the resolution of the problem of how to infer about concepts which are unknown at the semantic level. When the inference processes are stopped by a concept which is unknown at the semantic level but known (stored) at the associative level then concepts similar to an unknown are retrieved from the associative level. From retrieved concepts those that are known at the semantic level can be used as a substitute for an unknown concept thus enabling for the inference to be continued. For example if a concept beetle from the question “How many wheels has a beetle?” is unknown at the semantic level but known at the associative level than similar concept car retrieved from the associative level and known at the semantic level can be used as a substitute for an unknown concept “beetle”. This enables to continue the inference and conclude that beetle is similar to car and car mostly has four wheels. This way of thinking is natural to humans and is biologically, neurologically and psychologically plausible. But to this day best known knowledge schemes for representation of knowledge in uncertain domains don’t support this kind of reasoning. For example belief networks (Bayesian or probabilistic networks) [27-29] qualitative probabilistic networks [27], rule-based methods for uncertain reasoning, schemes based on the Dempster-Shafer theory [30], fuzzy logic and the fuzzy Petri net theory (FNP) [31]. All classical knowledge representation schemes that don’t support representing knowledge in uncertain domains like first order logic and higher order logics also don’t support this kind of reasoning. The system presented in this paper was designed to solve the problem of how to resolve unknown concepts in the inference processes.

Principal problem in the construction of the associative level is estimating and storing an exorbitant number of similarities between a large number of concepts what is often impractical and impossible. For example when storing 10^6 concepts at the associative level then 10^{12} similarities should be individually defined what is almost impossible. Studies [1, 2, 4, 5] suggest that stimuli (representing concepts) similarities in the brain are estimated based on the number of overlapping subsets of corresponding encoding neurons. It means that similarity between concepts is typically estimated as an inherent inborn property of the brain’s associative memory and it isn’t always learned through an experience from outside knowledge sources. Humans are able to estimate similarities between any two concepts even if they have never acquired knowledge about these similarities. Note that the inferences in the system can process only concepts stored at the associative level (c \in C) otherwise if concepts aren’t stored at the associative (c \notin C) the inference is stopped because no similarities to other concepts at the associative level exist. This isn’t significant limitation because the associative level has large storage capacity and this is psychologically plausible assumption. It corresponds to a situation when humans hear one word for the first time in their life and have no hint of its meaning. Not even humans are able to handle this situation without a help (they can use Google for example) and they seek outside knowledge queue to resolve this situation. The system presented in this paper replicates this behavior. When the system encounters concept unknown (not stored) at the associative level the inference is unable to continue until a human operator resolves this situation by manually specifying a similar corresponding concept stored at the associative level or by storing this concept at the associative level.

The system can possibly resolve situations when concept c_4 is unknown at the semantic level when (c_4 \notin D) but known at the associative level when (c_4 \in C). The situations when c_4 \notin C and consequently c_4 \notin D is unsolvable without an outside knowledge queue. Also note that it isn’t always possible to resolve unknown concepts at the semantic level. If a concept is stored in the associative level with no given similarity to any other stored concept at the associative level then it has indifferent similarity to all other concepts. For unknown concepts at the semantic level that have indifferent similarity to all other concepts at the associative level the inference can’t be resolved without a help from a human operator. This corresponds with situation when human states: “I have heard for it but I know nothing about it”. If a concept c_4 is stored at the associative level to a specific location determined by a given similarity to some other concept c_δ stored at the associative level then it has non-indifferent similarity to this
concept $c_r$. It than also follows that because $c_r$ is similar to $c_y$ it is also similar to concepts similar to the concept $c_r$ and so on recursively. Similar concepts are clustered together and chain of similarities is automatically established as a feature of a storage space. Note that the measure of similarity is graded from minimally to extremely as it will be described later.

The mathematical model that satisfies these requirements is Kanerva's SDM [14] and is used to implement the associative level of the system. The SDM model has direct corresponding elements in the model of a human associative memory and can replicate many aspects of a human information processing [14]. The SDM is used to store a human's knowledge about associations between concepts from the real world.

By using this biologically, neurologically and psychologically inspired memory model it is possible to give or define similarities among relatively few concepts but still to be able to efficiently estimate similarity among any two stored concepts at the associative memory as it will be described later. The SDM model is defined in the space of $\{0, 1\}^n$, $n \in \mathbb{N}$, where $\mathbb{N}$ is a set of the natural numbers, elements of which are n-dimensional vectors with binary components. These vectors are represented as points in an n-dimensional space. The number of points in an n-dimensional space is $N = 2^n$. $N$ is also used for naming the space itself, i.e. N-space. The main feature of N-space is its distribution, defined on the basis of the distances among the points. The distance $d(x,y)$ between two points $x$ and $y$ in N-space is defined as the number of corresponding vector components at which they differ, known as the Hamming distance. The distance is, by definition, an integer number in the range from 0 to n. The distance $d(x,y)$ can be used to express the similarity of the points $x$ and $y$. Biological measure of similarity between stimuli is expressed as a number of overlapping subsets of neurons what in the SDM naturally and straightforward translates to the measure of distance in the N-space. Corresponding vector binary components translate to corresponding subsets of neurons activations. Two points in the N-space that are close to each other are more similar. The concept of the address region is used at the associative level. The address region of an arbitrary address location $x$ in N-space is defined as a circle $O$ with the radius $r$ and the centre $x$. The address region of $x$ contains a set of points that are at most $r$ bits from $x$: $O(r,x) = \{y \mid d(x,y) \leq r\}$.

The basic characteristics of the above-described SDM model are: the similarity and the sparseness of the memory. The similarity, as mentioned above, is based on the distance between points. The sparseness is derived from the fact that the actual number of storage locations used is very few compared with $2^n$, $n \gg 1$. The storage locations are distributed randomly in the N-space and a unique address is assigned to each storage location. Even for a relatively small dimensionality of N-space (for example, $n = 100$) an exorbitant number of possible locations ($N = 2^{100}$) exists. Let us suppose that only a fraction of the possible address space (for example, $N' = 1,000,000$) is available and points are randomly distributed over the entire address space. Such a type of space is called a sparse memory. Correspondingly, addressing the N-space is now reduced to addressing the locations of the subspace $N'$, $N' \subset N$ called the N-space. The address location in N-space is represented by an n-dimensional address vector in the same way as in the N-space. Let $C$ be a set of abstract objects or concepts from the real world in the N-space at the associative level, which are the subject of the modelling. An element from $C$ can be represented with one or more points in the N'-space. A point in the N'-space is called a location when $N'$-space is represented as the SDM model. The concepts are clustered into groups of concepts based on a user's knowledge and/or an intuition. A concept can belong to one or more groups of concepts. Groups of concepts are used because it is natural for humans to organize similar concepts based on their characteristics. The assumption for the proposed model is that the number of points in the N'-space is much larger than the number of concepts.

A linguistic variable $L$ is used to express the similarity among the concepts. The values of the linguistic variable $L$ are from the following set \{minimally, mildly, moderately, considerably, very, extremely\}. The values of the linguistic variable $L$ can be transformed to the Hamming distance between two points in N'-space and vice versa. For example, in terms of the description of similarity with a value of the linguistic variable $L$, two concepts described as “very” similar will have a smaller distance between the corresponding points in N'-space than the concepts described as “minimally” similar.

B. Semantic level

Main task of the semantic level is to infer general knowledge about concepts by using the inheritance and the recognition inference processes. Principal problems with the inference processes at the semantic level are how to handle unknown concepts (i.e. $c_s \notin D$) and how to support the inferences with human’s knowledge about real or abstract facts from the real world that is uncertain, ambiguous, vague and fuzzy. How to handle with unknown concepts at the semantic level is solved by substituting them with retrieved similar concepts from the associative level that are known at the semantic level thus enabling inference to continue (i.e. robust reasoning). Problem of supporting inferences with human’s knowledge about real or abstract facts from the real world is solved with the help of the knowledge representation scheme based on the Fuzzy Petri Nets (FPN) theory called KRFPN [15]. The KRFPN knowledge scheme can be graphically represented in a similar way to the Petri nets: circles represent the places, while bars are used for the transitions. Concepts from D (stored in the KRFPN at the semantic level) are all necessarily present in the N'-space because D is subset of C, i.e. $D \subset C$. The uncertainty and the confidence related to facts, concepts and relationships between them are expressed by means of the fuzzy values of tokens ranging from 0 to 1. Tokens give dynamical properties to the KRFPN, and they are used to define its execution, i.e., by firing an enabled transition, tokens are removed from its input places and simultaneously, new tokens are created and distributed to its output places. The inheritance and the recognition, as the inference procedures defined for the KRFPN, use the dynamical properties of the KRFPN. Note that usually only a small proportion of concepts stored in the N'-space have corresponding place at the semantic level (KRFPN) i.e. number of storing locations at the semantic level is much smaller than at the associative level. A smaller number of stored concepts at the semantic level simplifies knowledge-base manipulation what is an advantage but makes it virtually impossible to deal with “real life” situations due to
a large human vocabulary and because typical situation descriptions are uncertain, ambiguous, vague and fuzzy. The psychological support for selected design of the semantic level that contains typically general knowledge and a smaller number of stored concepts compared to the associative level is presented in [11].

IV. STORAGE, RETRIEVAL AND INFERENCE PROCEDURES

In this Section algorithms used at every level will be listed with brief explanation but without formal description because subject of this paper is to describe only basic structural concepts of the proposed system. For the associative level following algorithms are used: the concept storing [33], the concept similarity estimation and the associative information retrieval algorithm [34]. The concept storing algorithm is used to store concepts in the N'-space. Optionally similarities to other stored concepts are expressed with values of the linguistic variable. Values of the linguistic variable are transformed to distances in the N'-space that are used to store concepts. Distances in the N'-space encode similarities. Distances between two concepts in the N'-space will be inversely proportional to corresponding similarity. The concept similarity estimation algorithm is used to determine similarity between two concepts stored in the N'-space based on the distance between them. The result is expressed with the value of the linguistic variable. The associative information retrieval algorithm is used when resolving unknown concepts at the semantic level. Unknown concepts are substituted with similar concepts that are retrieved from the associative level and are known at the semantic level thus enabling the inference to continue. In the retrieval, the similarity between concepts is expressed with the value of the linguistic variable.

For the semantic level following algorithms are used: the inheritance and recognition algorithm. In general, inheritance is a form of reasoning that allows an agent to infer the properties of a concept on the basis of the properties of its ancestors in the network’s hierarchical structure [28]. More precisely, the inheritance can be described as the process of determining the properties of a concept, by looking up the properties that are locally attached to the concept. If such local information is not available (or is insufficient), the process will continue by looking up properties attached to the concepts that lie at higher levels in the conceptual hierarchy.

The entry point for an inheritance process (Fig. 2) is a known concept of interest and the output are its properties. The entry point for the recognition process (Fig. 2) is partial information about an unknown concept c_y. By means of the recognition process, the output “c_y is concept c_y” is obtained, where c_y is the best matching among concepts from D. Recognition process can be considered as an inverse process to the inheritance.

The inheritance procedure in the KRFPN is based on its dynamical properties and the determination of the inheritance set. The inheritance set for the KRFPN is represented as an inheritance tree that is based on concepts similar to the reachability set of the ordinary Petri nets (PNs). The reachability set is defined as the smallest set of all the reachable distributions of tokens starting from an initial distribution of tokens for the PN and recursively applying the firing of enabled transitions for immediately reachable distributions of tokens.

Key points of the inheritance and the recognition process are the inheritance tree and a function that maps concepts of interest into corresponding places thus determining initial markings (i.e. it puts tokens in the corresponding places). In the KRFPN scheme the inheritance tree represents results of all sequences of firing of enabled transitions, starting with initial marking. If we are interested in properties of a concept of interest c_x and if c_x ∉ D, the process of inheritance will stop because a function that maps a concept of interest into a corresponding place isn’t defined. This problem is resolved by substituting an unknown concept with similar concepts retrieved from the associative level. For retrieved concepts from the associative level that are present at the semantic level (c_x ∈ D) the inheritance can be continued. Note that everything said about the inheritance can be applied to the recognition process which is dual to the inheritance.

By introducing the associative level more diverse and more efficient models of inheritance and recognition all having neurological and psychological explanation can be obtained:

a) A “pure” associative inference (“pure” API) or so-called recall procedure (Fig. 3). If a concept of interest c_x exists in the associative level then similar concepts, with distances from c_x smaller than r bits, are retrieved from the associative level by means of the associative information retrieval algorithm. The procedure is similar to human behaviour in the process of recalling similar concepts for incoming stimuli from sensor modalities (i.e. concepts of interest). For example, the concept “elephant” may associate somebody to “ivory”, “Africa” and so on.

b) Associative recall based on transfer activity through intersected circles (TAPI), (Fig. 4). A concept of interest c_x is used for retrieving similar concepts, with distances from c_x smaller than r bits, from the associative level by means of the associative information retrieval algorithm. Retrieved concepts are then used as new concepts of interest to recursively retrieve new “non-retrieved” similar concepts. The above process is performed at the associative level.
c) “Pure” inheritance procedure (“pure” IP) is defined at the semantic level and implemented by the KEFPN scheme (Fig. 5). For a concept of interest $c_r \in D$ a corresponding place $p_r$ in the KEFPN scheme is obtained by using a function that maps a concept of interest into a corresponding place. A place $p_r$ is defined as a place with token and it defines initial marking for constructing the inheritance tree. The “pure” inheritance is described in detail in [32]. If a concept of interest isn’t stored at the semantic level $c_r \notin D$, then a corresponding place in the KEFPN scheme isn’t defined and the process of inheritance is stopped.

![Fig. 5. A “pure” inheritance procedure IP.](image1)

d) “Mixed” inheritance procedure (“mixed” IP) is based on co-operation between the associative and the semantic level. There are three main cases:

i) For a concept of interest $c_r \in D$, similar concepts are retrieved from the associative level by means of the associative information retrieval algorithm (Fig. 6). A concept of interest and all retrieved concepts for which a function that maps concepts of interest into corresponding places is defined (elements of D) define initial markings for constructing inheritance trees at the semantic level. These initial markings define many sources of activity which are used in the inheritance procedure at semantic level.

![Fig. 6. Mixed inheritance procedure (c_r \in D) IP.](image2)

ii) For a concept of interest $c_r$ known (stored) at the associative level but unknown at the semantic level $c_r \in C$ and $c_r \notin D$ (Fig. 7), a function that maps concepts of interest into corresponding places is not defined. By using associative information retrieval algorithm similar concepts are retrieved from the associative level. If some of retrieved concepts are elements of the semantic level then a function that maps concepts of interest into corresponding places in the KEFPN scheme is defined for them so they could be used to define initial markings at the semantic level. These initial markings define many sources of activity which are used in the inheritance and the recognition processes at the semantic level.

![Fig. 7. Mixed inheritance procedure (c_r \in C, c_r \notin D).](image3)

iii) For a concept of interest $c_r$ stored at the associative level ($c_r \in C$) but unknown at the semantic level ($c_r \notin D$) (Fig. 8), the combination of the associative inference procedure “pure” API and TAPI are used to obtain initial tokens distribution. Initial token distributions define multiple sources of activity at the semantic level (Fig. 8) that activate inheritance procedures.

![Fig. 8. The combination of the associative inference procedure “pure” API and TAPI.](image4)

V. FUTURE WORK

A future work will include the application of the hierarchical heterogeneous knowledge-base system for intelligent document and web search. The ultimate goal is to create search engine able to replicate human information processing abilities. This robust and efficient search engine would significantly enhance quality of search results and reduce a time for obtaining desired results.

VI. CONCLUSION

In this paper the hierarchical heterogeneous knowledge-base system is presented. The system was inspired by biological, neurological and psychological models obtained by analyzing how the human brain abstracts knowledge from the interactions with the environment. It has two levels: the lower associative and the higher semantic. The system supports manipulation with human’s knowledge about real or abstract facts from the real world that are uncertain, ambiguous, vague and fuzzy. Main contribution of this paper is contained in a biologically, neurologically and psychologically inspired solution of the problem how to process novel concepts in the semantic description of some general knowledge from the real
world. Unknown concepts at the semantic level trigger similarity based retrieval of concepts at the lower associative level that are possibly present at the semantic level so they are used to substitute an unknown concepts thus enabling inference procedure to continue. This solution enables efficient and time effective inference where classical network based knowledge representation scheme would fail and respond with an answer “Unknown concept”. The system enables robust and human like inference process capabilities.

REFERENCES


