Robust Initialization for Reasoning Procedures in a Hierarchical Heterogeneous Knowledge-Base

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Abstract—**This paper describes a model of a hierarchical, heterogeneous knowledge-base. The proposed model consists of an associative level that is implemented by a Kanerva-like sparse distributed memory (SDM) and a semantic level realized by a knowledge-representation scheme based on the Fuzzy Petri Net theory. The levels are interconnected with forward and backward connections that are used for the robust initialization of multi-reasoning procedures (inheritance, recognition and intersection search) at the semantic level. Multi-reasoning supports reasoning for an unknown concept (i.e., a concept that is not defined at the semantic level), parallel reasoning for more than one concept that is obtained by forward connections from the associative level and used for multiple initialization, and the chaining of associative information retrieval and the reasoning process using forward and backward connections. An example of the initialization of the multi-inheritance procedure is given.**

Keywords: hierarchical knowledge-base, associative level, semantic level, Fuzzy Petri Net, reasoning, inheritance.

I. INTRODUCTION

The motivation for the presented research is to design a model that supports manipulation with human knowledge about real or abstract concepts obtained from the real world that are fuzzy uncertain, vague and ambiguous. The approach of this work was inspired by biological, neurological and psychological models obtained by analyzing how human and animal brains abstract, process, store and retrieve knowledge from interactions with the environment. In general, neuro-anatomical studies have concluded that all cortical systems display a significant degree of hierarchical organization [1-4]. The 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]. The 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, and backward connections are more divergent and they are used when processing unknown stimuli. On the other hand, psychological support for a hierarchical and heterogeneous multilevel organization of a knowledge-base can be found in a study by Piaget and Inhelder [6], who 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. Hierarchical learning systems have been demonstrated by the phenomena discovered and studied using Gestalt psychology [7, 8].

A brief overview of the related work is given in the following paragraph. In [9] a heterogeneous, hierarchical knowledge-base model called HETHI is described. It consists of one level of the Kanerva-like Sparse Distributed Memory (SDM) that performs the associative information retrieval process and supports the initialization of the inheritance process at higher levels, the semantic and rule-based levels. In [10], 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. In [11] 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. In [12] the SDM is used for multilevel cognitive tasks. The SDM is organized to link low-level information and high-level correlations. In [13] issues in developing cognitive architectures, called CLARION, as generic computational models of cognition are discussed in detail. It consists of two levels: the top level that captures explicit processes and the bottom level that handles implicit processes. It provides a conceptual reasoning capability.

Based on biological, neurological and psychological studies [1-8], a hierarchical, heterogeneous knowledge-base model is proposed in this paper. The proposed model consists of two levels: the associative level, realized by Kanerva-like SDM, and the semantic level, realized by Fuzzy Petri Nets. The paper describes the architecture of the fuzzy-associative hierarchical knowledge-base and the robust initialization for multi-reasoning at the semantic level.

II. ARHITECTURE OF THE HIERARCHICAL HETEROGENEOUS KNOWLEDGE-BASE MODEL

The proposed hierarchical, heterogeneous knowledge-base consists of associative and semantic levels interconnected with forward and backward connections and a graphical user interface (GUI) (Fig.1).

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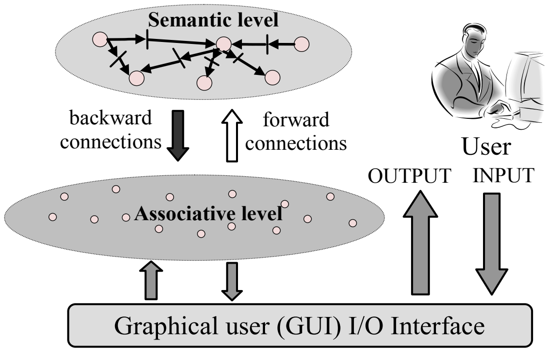


Figure 1. The architecture of the proposed model.

A. Associative level

The associative level of the knowledge-base is implemented with the use of concepts related to the addressing mechanism of the Kanerva's SDM [14]. 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 the SDM model are n-dimensional vectors with binary components that are represented as points in an n-dimensional space. The number of points in an n-dimensional space is $N = 2^n$. However, 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 two basic characteristics of the above-described SDM model are: the *similarity* and the *sparseness* of the memory. *Similarity* is based on the distance between the points in the N-space. *Sparseness* is derived from the fact that the actual number of points used is very few compared with 2^n, $n >> 1$, and they are distributed randomly in the N-space. Even for a relatively small dimensionality of the N-space (for example, $n = 100$) an enormous number of possible locations ($N = 2^{100}$) exists. Let us suppose that only a fraction of the possible points (for example, $N' = 10^6$) is available and they are randomly distributed over the entire N-space. Such a type of space is called a sparse memory.

At the associative level of our model, which is based on Kanerva's SDM, we use four features: address, location, concept and address region. The address of a memory location in the N'-space is represented by an n-bit vector that defines a location where a concept is stored. The address region of an arbitrary address a of location x in the N'-space is defined as a circle O with a radius r and a centre a. The address region of a contains a set of points that satisfy the following relation: $O(r,a)=\{a' \mid d(a,a') \leq r\}$, where $d(a,a')$ is the Hamming distance between address a and a'.

The distance $d(a,a')$ is used to express the similarity between the concepts that are stored in locations defined by the addresses a and a'.

A multi-set of concepts stored at the associative level is denoted as C^A, and the set of concepts stored at the semantic level is denoted by C^S. Note that the cardinality of C^A is much larger than the cardinality of C^S:

$$\text{card}(C^A) >> \text{card}(C^S), \text{ and } C^S \subset C^A.$$

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: {*not*, *minimally, minorly, more-or-less, moderately, considerably, very, extremely, identical*}. The values of the linguistic variable L are transformed to the intervals of the Hamming distances (see TABLE I).

TABLE I. MAPPING OF THE VALUES OF THE LINGUISTIC VARIABLE L TO THE HAMMING DISTANCES AND CONFIDENCE VALUES

Values of the linguistic variable *L*; intervals	**Interval of Hamming distances $[d_{min}, d_{max}]$**	**Initial confidence value, *conf***	**$[d_{min}, d_{max}]$, $n = 100$, $p = 10^{-4}$, $r_p = 31$, $\rho = 3$**
identical [1.0, 1.0]	$[0, 0]$	1	[0, 0]
extremely [0.95, 0.99]	$[1, r_p]$	0.95	[1, 31]
very [0.80, 0.94]	$[r_p+1, r_p+\rho]$	0.80	[32, 34]
considerably [0.65, 0.93]	$[r_p+\rho+1, r_p+2\cdot\rho]$	0.65	[35, 37]
moderately [0.45, 0.64]	$[r_p+2\cdot\rho+1, r_p+3\cdot\rho]$	0.45	[38, 40]
more-or-less [0.30, 0.44]	$[r_p+3\cdot\rho+1, r_p+4\cdot\rho]$	0.30	[41,43]
minorly [0.10, 0.29]	$[r_p+4\cdot\rho+1, r_p+5\cdot\rho]$	0.10	[44, 46]
minimally [0.01, 0.09]	$[r_p+5\cdot\rho+1, r_p+6\cdot\rho]$	0.01	[47, 49]
not [0.0, 0.0]	$[r_p+6\cdot\rho+1, n]$	0.00	[50, 100]

The radius r_p (TABLE I) defines an address region $O(r_p,a)$ represented by an n-dimensional sphere, which contains the number of addresses a' equal to an average p proportion of the total number of addresses in the N'-space:

$$O(r_p,a)=\{a' \mid d(a,a') \leq r_p\}.$$

The radius r_p is obtained from [14] based on the number of dimensions of the SDM and the proportion p. This proportion p is determined experimentally and its value is 10^{-4}. In our case for $n = 100$, $N' = 10^6$ and $p = 10^{-4}$, the radius r_p is 31, which means in the address region $O(31,a)$ there are $10^6 \cdot 10^{-4} = 100$ addresses. ρ defines the incremental change of intervals of the Hamming distances associated with the values of the linguistic variable L (see TABLE I) and it is determined experimentally based on the value of n. The value of ρ is 3 for $n = 100$. The value of the linguistic variable is represented by an interval of a confidence values. It expresses our strength of belief in the meaning of the connection between concepts. The column "Initial confidence value *conf*" (TABLE I) defines values of initialized concepts, i.e. initial values of tokens (see Section III. B). Note that the initial value *conf* for the concept of interest is always 1 if $c_i \in C^S$.

The values of the linguistic variables in TABLE I are determined based on [15], while others are obtained experimentally.

The main task of the associative level is to enable the robust and fuzzy initialization of multi-reasoning processes at the semantic level. The robust initialization means that it is possible to start multi-reasoning for the following two cases:

i) the concept of interest is present at the semantic level,

ii) the concept of interest is not present at the semantic level.

In case i) it is possible to use, besides the defined concept of interest, also concepts obtained from the associative level based on the similarity among the defined concept and others stored at the associative level. These concepts are transferred to the semantic level and used for initialization of the process of multi-reasoning.

In case ii) for the initialization of multi-reasoning it is necessary to use concepts obtained from the associative level based on the similarity among the concept of interest (which is only stored at the associative level) and other concepts at the associative level. The distances between the concept of interest and other concepts will be used at the semantic level for a determination of the fuzzy value, which represents the confidence value of the initialized concepts. The “initialized concept” is the concept transferred from the associative level to the semantic level and it is an element of the set C^S.

In both cases the initialization is possible owning to forward and backward connections that exist between the associative and semantic levels (see Fig. 1) and the fact that the number of stored concepts at the associative level is a few orders of magnitude larger than at the semantic level. The semantic level is implemented by the structured network-based fuzzy-knowledge representation scheme [16] and its storage capacity is therefore limited.

Note that in “classical” single-level knowledge-bases it is not possible to start the reasoning process when the concept of interest is unknown. i.e., it is not an element of C^S. The multiple reasoning is also not possible.

B. Semantic level

Multi-reasoning that is performed at the semantic level supports:

i) reasoning for an unknown concept (i.e., a concept that is not defined at the semantic level);

ii) parallel reasoning for more than one concept that is obtained by the forward connections from the associative level and used for multiple initialization;

iii) chaining of the associative information retrieval and reasoning process using forward and backward connections – using intermediate or final results of a reasoning process as the associative queries for new initializations of the reasoning process.

The semantic level is implemented by a knowledge-representation scheme based on the Fuzzy Petri Net theory called KRFPN. Here we present a brief description of the KRFPN relevant for this paper, for details see [17]. The KRFPN is defined as being 13-tuple:

$$\text{KRFPN} = (P, T, I, O, M, \Omega, \mu, f_T, f_M, \alpha, \beta, \text{Contr}, \lambda), \quad (1)$$

where P, T, I, O, M, Ω, μ, f_T, and f_M are components of a generalized Fuzzy Petri Net (FPN), as follows:

$P = \{p_1, p_2, \dots, p_n\}$ is a finite set of places,

$T = \{t_1, t_2, \dots, t_m\}$ is a finite set of transitions,

$P \cap T = \varnothing$,

$I: T \rightarrow P^\infty$ is an input function, a mapping from transitions to bags of places,

$O: T \rightarrow P^\infty$ is an output function, a mapping from transitions to bags of places,

$M = \{m_1, m_2, \dots, m_q\}$, $1 \le q < \infty$, is a set of tokens. Note that the corresponding value f_M: $m_i \rightarrow [0, 1]$ is associated with each token m_i, $1 \le i \le q$.

Ω: $P \rightarrow \wp(M)$, is a mapping, from P to $\wp(M)$, called a distribution of tokens, where $\wp(M)$ denotes the power set of M. Using Ω_0 we denote the initial distribution of tokens in the places of the FPN.

μ: $P \rightarrow \mathbb{N}_0$ is a marking, a mapping from places to non-negative integers $\mathbb{N}_0$. A mapping μ can be represented as an *n*-component vector $\boldsymbol{\mu} = (\mu_1, \mu_2, \dots, \mu_n)$, where *n* is a cardinality of the set P. Obviously, $\mu(p_i) = \mu_i$, and $\mu(p_i)$ denotes the number of tokens in the place p_i. An initial marking is denoted by the vector $\boldsymbol{\mu_0}$.

f_T: $T \rightarrow [0, 1]$ is an association function, a mapping from transitions to real values between zero and one.

f_M: $M \rightarrow [0, 1]$ is an association function, a mapping from tokens to real values between zero and one.

The functions α and β give a semantic interpretation to the scheme.

The bijective function α: $P \rightarrow C^S$ maps a set of places onto a set of concepts C^S. The set of concepts C^S consists of the formal objects used for representing objects and facts from the agent’s world. The elements from $C^S = C_1^S \cup C_2^S \cup C_3^S$ are as follows: elements that denote the classes or categories of objects and represent higher levels of abstraction (C_1^S), elements corresponding to the individual objects as instances of the classes (C_2^S) and those elements representing the intrinsic properties of the concepts or values of these properties (C_3^S).

The surjective function β: $T \rightarrow \Sigma$ associates a description of the relationship among facts and objects to every transition $t_i \in T$; $i = 1, 2, \dots, m$, where m is a cardinality of the set T. The set $\Sigma = \Sigma_1 \cup \Sigma_2 \cup \Sigma_3$ consists of elements corresponding to the relationships between the concepts used for partial ordering of the set of concepts (Σ_1), the elements used to specify the types of properties to which values from the subset C_3^S are assigned (Σ_2), and the elements corresponding to the relationships between the concepts, but not used for hierarchical structuring (Σ_3).

The semantic interpretation requires the introduction of a set of contradictions Contr [17].

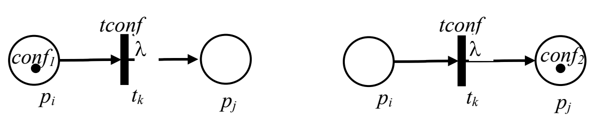
$\lambda \in [0, 1]$ is a threshold value related to the firing of an enabled transition.

The inverse function α^{-1}: $C^S \rightarrow P$, and the generalized inverse function β^{-1}: $\Sigma \rightarrow \tau$; $\tau \subseteq T$ are defined in the KRFPN scheme.

The scheme can be represented by a bipartite directed multi-graph containing two types of nodes: places and transitions. Graphically, the circles represent places while the bars are used for transitions. The connections among the places and transitions are defined by means of the input and output functions of the marked Petri net [18]. In the scheme, concepts are assigned to the places. The relations that represent concept properties, spatial, temporal, spatio-temporal relationships, and interclass relations are assigned to transitions. The fuzziness of the scheme is based on fuzzy tokens and fuzzy transitions.

The fuzzy reasoning procedures at the semantic level are based on the dynamical properties of the FPN defined by firing the enabled transitions. The definitions of an enabled transition and firing are given in [18]. Fuzzy tokens give the dynamic to the FPNs [17] by its moving from place to place and changing its fuzzy values. Fig. 2 shows the generic form of a chunk of knowledge and illustrates the firing of the enabled transitions. For example, if the initial value of the fuzzy token at the input place p_i is obtained by the function f_M and it is denoted as $conf_1$ and the fuzzy value assigned to transition t_k is determined by the function f_T and denoted $tconf$, after firing the enabled transition t_k, the new confidence value of the token in the output place p_j is $conf_2 = conf_1 \cdot tconf$.

The transition t_k is enabled if there is a fuzzy token in the input place and if its value $conf_1$ is greater than the firing threshold λ.



a) Before firing; $conf_1 > \lambda$ b) After firing; $conf_2 = conf_1 \cdot tconf$

Figure 2. Firing an enabled transition.

III. FUZZY MULTI-REASONING

The automatic reasoning procedures defined at the semantic level are inheritance, recognition and intersection search. The inheritance is a form of reasoning that allows an agent to infer the properties of a concept of interest on the basis of the properties that are locally attached to the concept as well as the properties of its ancestors in the hierarchical structures of the knowledge-base. The formal definition and the algorithm of the fuzzy inheritance procedure are given in [17].

Recognition is the dual of the inheritance problem – the input is a set of properties (associated with a confidence value of each property) of an unknown concept and the output of the recognition procedure are concepts with confidence values that match the unknown concept. The recognition algorithm is formally described in [17], [19].

The intersection search allows relationships to be found between two concepts by "spreading activities" from the places (called patriarch nodes) that correspond to the concepts and searching the concepts, i.e., the places (called intersection nodes) where the activities meet [20].

In this section we describe in detail the fuzzy pre-initialization and initialization that are essential for the fuzzy multi-inheritance procedure. A similar algorithm can be applied for multi-recognition and intersection search.

A. Fuzzy Pre-initialization Algorithm for Multi-inheritance

INPUT: A concept of interest c_i and a value l of the linguistic variable L. Select single- or multi-reasoning.

OUTPUT: Pairs of concepts and corresponding confidence values for the initialization of the reasoning procedure.

STEP 1: Checking if the concept of interest c_i is stored at the associative level ($c_i \in C^A$).

1.1) Based on associative retrieval with the query c_i find all the locations x_j , $j = 1, 2, \ldots , m$, and form a list of corresponding addresses a_j, $j = 1, 2, \ldots , m$, of the locations.

1.2) IF the address list is empty (i.e., the concept c_i is not found at the associative level; $c_i \notin C^A$) THEN send the message "c_i is an unknown concept" and STOP the pre-initialization procedure.

STEP 2: Checking if the concept of interest c_i is present at the semantic level ($c_i \in C^S$).

2.1) Use a forward connection to transfer the concept of interest c_i from the associative level to the semantic level.

2.2) IF $c_i \in C^S$ AND a single-reasoning is selected THEN the corresponding fuzzy-confidence value of the concept of interest is $conf = 1$ and initialize reasoning procedure with (c_i , 1) as defined in the Section III. B and STOP the pre-initialization procedure.

2.3) IF $c_i \notin C^S$ AND a single-reasoning is selected THEN send the message "pre-initialization for the c_i isn't possible for single-reasoning" and STOP the pre-initialization procedure.

2.4) IF ($c_i \in C^S$ OR $c_i \notin C^S$) AND multi-reasoning is selected THEN use backward connections to transfer the c_i back to the associative level.

STEP 3: Finding similar concepts to the concept of interest c_i at the associative level.

3.1) For every address a_j , $j = 1, 2, \ldots , m$, from the address list obtained in STEP 1.1 create n-dimensional spheres at the associative level with a radius r and centres a_j , $j = 1, 2, \ldots , m$. Note that r is defined by means of the value l of the linguistic variable L (see TABLE I) in such a way that its upper boundary (d_{max}) of an interval of the Hamming distances [d_{min}, d_{max}] is taken as r.

3.2) For all n-dimensional spheres find locations x_k, $k = 1, 2, \dots, q$, where the concepts c_k are stored, with the corresponding addresses a_k that satisfy the following relation:
$O(\mathrm{r}, a_j) = \{a_k \mid \mathrm{d}(a_j, a_k) \le \mathrm{r}\}$, $j = 1, 2, \dots, m$ and $k = 1, 2, \dots, q$, where d is the Hamming distance.

STEP 4: Determining the initial confidence values for the reasoning procedure at the semantic level.

4.1) All concepts c_k that are obtained in STEP 3.2. together with the corresponding distances $\mathrm{d}(a_j, a_k)$, $j = 1, 2, \dots, m$ and $k = 1, 2, \dots, q$, are transferred by means of forward connections to the semantic level.

4.2) Only for $c_k \in C^S$ based on the value of $\mathrm{d}(a_j, a_k)$ select the initial confidence value $conf_k$ as follows:

In TABLE I find the row with an interval for which $\mathrm{d}(a_j, a_k) \in [d_{min}, d_{max}]$ is satisfied. Take the initial confidence value that lies in the same row of TABLE I.

4.3) Use the $s \le q$ pairs (c_k, $conf_k$) to initialize the multi-reasoning procedure defined in Section III. B.

B. Initialization of Multi-inheritance

The pre-initialization algorithm generates the list of pairs (c_k, $conf_k$), $k = 1, 2, \dots, s$ that is the input to the initialization procedure for multi-reasoning.

For each concept $c_k \in C^S$, $k = 1, 2, \dots, s$ (i.e., initialized concept) from the above list of pairs, by using the inverse function α^{-1} (see Section II. B), find the corresponding place p_j:

$$\alpha^{-1}: c_k \to p_j,$$

where $p_j \in P$, $j \le n$, where n is the number of places (i.e., the cardinality of the set C^S).

For p_j corresponding to c_k define the initial marking $\mu_0^k = (\mu_1, \mu_2, \dots, \mu_n)$, where for $k = 1, 2, \dots, s$,

$$\mu_i = \begin{cases} 1 & \text{for } i = j \\ 0 & \text{for } i \ne j \end{cases}, \ i = 1, 2, \dots, n$$

Define the initial distribution of tokens $\Omega_0^k = (\varnothing, \varnothing, \dots \{(p_j, conf_k)\}, \dots, \varnothing, \varnothing)$, i.e., a token m with the initial value $conf_k$ (obtained by f_M: m $\to conf_k$) is put at the place p_j.

Note that every pair (c_k, $conf_k$), $k = 1, 2, \dots, s$ defines one initial distribution of tokens Ω_0^k and the multi-inheritance procedure is performed in parallel for each Ω_0^k.

For example, the next step for the multi-inheritance procedure is the construction of $s \ge 1$ inheritance trees, or for the multi-recognition procedure the construction $s \ge 1$ recognition trees [17].

IV. AN EXAMPLE

Let us suppose that N'-space is created as a subspace of N-space; $N=2^n$; $n = 100$. The N'-space is defined by the following parameters: $n = 100$, $N' = 10^6$, $p = 10^{-4}$. Based on selected values of p and n, the radius $r_p = 31$ is determined [14].

Some of the concepts used in this simple example are depicted in TABLE II and Fig. 3. This example is only used for illustrative purposes.

In general, the associative connections between concepts can be obtained by psychological experiments, as described in [21] or by an expert. The concepts from the example were stored at the associative level by means of the concept-storing algorithm presented in [22]. A partial list of addresses of the locations where concepts used in the example are stored at the associative level (obtained by the program simulator described in [23]) is depicted in TABLE II.

TABLE II. PARTIAL LIST OF ADDRESSES OF LOCATIONS WHERE CONCEPTS USED IN THE EXAMPLE ARE STORED AT THE ASSOCIATIVE LEVEL

Location	C^A	**Concepts**	a_i	**Store address a_i (100 bit vector, represented as hex number)**
x_1	c_1	raven	a_1	D091E7E12082E9D2A1E218F84
x_2	c_2	bird	a_2	E8D467F026D26BD2FBB950E3C
x_3	c_3	pigeon	a_3	D086D23140880BF677C3A8714
x_4	c_4	scarecrow	a_4	59BA65AB6498E76229DC78C15
x_5	c_5	mammal	a_5	D1B10DA70C3843E52B24C9A40
x_6	c_6	witch	a_6	8DEFA4A14BE24B96A1E7529D4
x_7	c_7	crow	a_7	E065W0A4E9C65B96346718116
x_8	c_8	straw	a_8	E7DB36E123A9319E72A3FC388
x_9	c_9	mouse	a_9	B8A8154D6CE76EB5C5225DEE1
x_{10}	c_{10}	corn	a_{10}	B232A21AE074F1AB14E649DDC
x_{11}	c_{11}	egg	a_{11}	40038E8842ECEF8B72AE28EA4

For example, from TABLE II the Hamming distance between the addresses where the concepts "raven" (a_1) and "bird" (a_2) are stored is $\mathrm{d}(a_1, a_2) = 31$. It means that they are "*extremely*" similar (see TABLE I).

An example of the fuzzy initialization for multi-reasoning procedures is presented as follows:

INPUT: A concept of interest c_i = "raven", l = "*considerably*". Select multi-reasoning.

STEP 1: Checking if the "raven" $\in C^A$.

1.1) Based on associative retrieval with a query "raven" the location x_1 is found, and a list of corresponding addresses (a_1) is formed (see TABLE II).

STEP 2: Checking if the "raven" $\in C^S$.

2.1) Use forward connections to transfer the "raven" from the associative level to the semantic level.

2.4) $c_i \notin C^S$ but multi-reasoning is selected so the "raven" is transferred back to the associative level.

STEP 3: Finding similar concepts to the "raven" at the associative level.

3.1) For address a_1, from the address list obtained in STEP 1.1 an n-dimensional sphere O_1 is created with radius r = 37 and centre a_1. The radius r = 37 is obtained by means of the value *considerably* of the linguistic variable L (see TABLE I) in such a way that r is taken as upper boundary of the corresponding interval of the Hamming distances [35, 37].

3.2) From the n-dimensional sphere $O_1(37, a_1)$ the locations x_2, x_3, x_4, x_6 are found where the concepts c_2 = "bird", c_3 = "pigeon", c_4 = "scarecrow" and c_6 = "witch" are stored, with the corresponding addresses a_2, a_3, a_4, a_6 that satisfy the following relations: $O_1(37, a_1) = \{a_k \mid d(a_1, a_k) \leq 37$, $k = 2, 3, 4, 6$ where d is the Hamming distance. Note that $d(a_1, a_2) = 31$, $d(a_1, a_3) = 34$, $d(a_1, a_4) = 37$ and $d(a_1, a_6) = 36$.

STEP 4: Determining the initial confidence values for the reasoning procedure at the semantic level.

4.1) The pairs $(c_2, 31)$, $(c_3, 34)$, $(c_4, 37)$ and $(c_6, 36)$ are transferred by means of forward connections to the semantic level.

4.2) $c_2, c_3, c_4 \in C^S$, $c_6 \notin C^S$ (see Fig. 3). From TABLE I the initial confidence values are determined for c_2, c_3, c_4. (For example, for c_2 and $d(a_1, a_2) = 31$, and $d(a_1, a_2) \in [0, 31]$ the $conf_2$ is 0.95, see TABLE I).

4.3) Use three pairs $(c_2, 0.95)$, $(c_3, 0.80)$, and $(c_4, 0.65)$ to initialize multi-reasoning procedure.

OUTPUT: ("bird", 0.95), ("pigeon", 0.80), ("scarecrow", 0.65).

Here we describe the initialization only for the first pair, i.e., ("bird", 0.95):

Based on the bijective function $\alpha: P \rightarrow C^S$ that maps a set of places onto a set of concepts C^S (see Fig. 3.):

$\alpha: p_1 \rightarrow$ bird; $\alpha: p_2 \rightarrow$pigeon; $\alpha: p_3 \rightarrow$ owl; $\alpha: p_4 \rightarrow$ scarecrow; $\alpha: p_5 \rightarrow$ nest; … .

and by using the inverse function α^{-1} the corresponding place p_1 is obtained: α^{-1}: bird $\rightarrow p_1$.

For p_1 define the initial marking $\mu_0^2 = (1, 0, \ldots, 0)$.

Define the initial distribution of tokens $\Omega_0^2 = (\{(p_1, 0.95)\}, \varnothing, \varnothing, \ldots, \varnothing, \varnothing)$.

In a similar way for the pairs ("pigeon", 0.80), ("scarecrow", 0.65) the initial distributions of tokens are obtained $\Omega_0^3 = (\varnothing, \{(p_2, 0.80)\}, \varnothing, \ldots, \varnothing, \varnothing)$, $\Omega_0^4 = (\varnothing, \varnothing, \varnothing, \{(p_4, 0.65)\}, \varnothing, \ldots, \varnothing, \varnothing)$ (see Fig. 3.). The reasoning procedure is performed in parallel for each Ω_0^2, Ω_0^3, Ω_0^4 (see Fig. 3.).

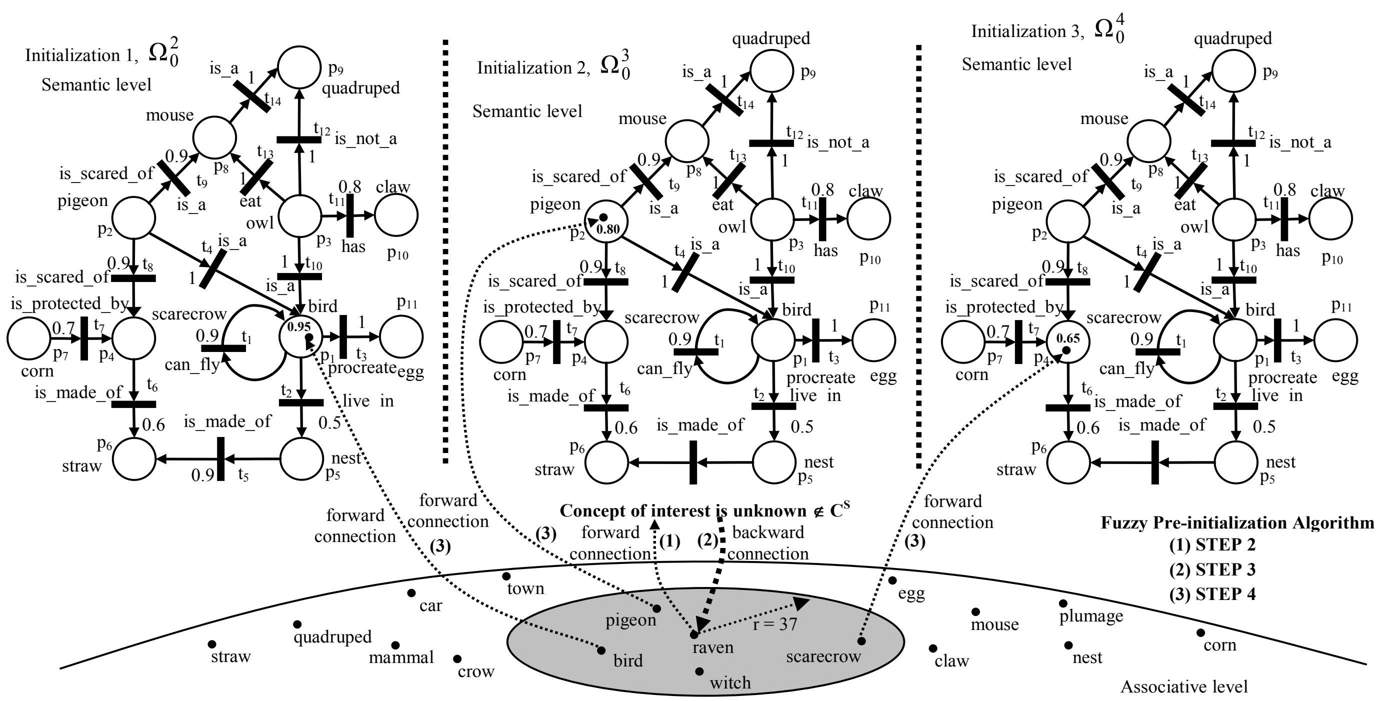


Figure 3. Example of initialization.

V. CONCLUSION

A hierarchical, heterogeneous, knowledge-base model that is inspired by biological, neurological and psychological studies is proposed in this paper. It consists of an associative level and a semantic level. The associative level that is implemented by the Kanerva-like SDM has a few orders of magnitude larger capacity than the capacity of the semantic level. This fact enables a robust initialization that supports multi-reasoning procedures at the semantic level: inheritance, recognition and intersection search. Multi-reasoning also supports the inference procedures for a concept that is not defined at the semantic level, parallel reasoning for more than one concept that is obtained by forward connections from the associative level, and chaining of the associative information retrieval and reasoning process by using the intermediate or final results of a reasoning process. Such final or intermediate results are used for the associative queries for new initializations of a reasoning process. The proposed model is used for the design of an automatic image-annotation system in order to exploit the massive image information and to support techniques for analyzing the image content to facilitate indexing and retrieval [24]. The proposed model is suitable for data mining and intelligent document and web searches. Future work will consist of a further experimental validation of the proposed model for above-mentioned applications.

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