Information Gathering on the Internet Using a Distributed Intelligent Agent Model with Multi-Granular Linguistic Information

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Abstract

Information gathering in Internet is a complex activity. Find the appropriate information, required for the users, on the World Wide Web is not a simple task. Then, Internet users need tools to assist them to obtain the information required. One possibility consists of using distributed intelligent agents in the information gathering process that help the users to cope with the mass of content available on the World Wide Web.

The communication between users and agents is very important to the information gathering process be successful. The great variety of representations of the information in Internet is the main obstacle to this communication. The use of the linguistic information provides a more flexibility in the communication among agents and between agents and users. In this paper we propose a distributed intelligent model for gathering information on the Internet where the agents and users may communicate among them using a multi-granular linguistic model. This model provides a greater flexibility and several advantages in the user-system interaction.

Keywords: Internet, information retrieval, intelligent agents, computing with words, linguistic modelling.

1 Introduction

Information gathering on Internet is a very important, widely studied and hotly debated topic. The exponential increase in Web sites and Web documents is contributing to that Internet users not being able to find the information they seek in a simple and timely manner. There are many publicly available search engines, but users are not necessarily satisfied with the different formats for inputting queries, speeds of retrieval, presentation formats of the retrieval results, and quality of retrieved information. Therefore, users are in need of tools to help them cope with the mass of content available on the World Wide Web [17, 18].

A solution consists in to assist Internet users in information gathering processes by means of distributed intelligent agents in order to find the fittest information to their information needs [3, 9, 25, 28, 32]. Several proposals about intelligent software agents have been emerging in the recent last years to improve different tasks related to *networking* among them the Information Retrieval. But the lack of connection and communication among agents have lead to a decrease in the quality and suitability of the retrieved information besides the efficiency of the system in the recovering and filtering task. The great variety of representations and evaluations of the information in the Internet is the main obstacle to this communication, and the problem becomes more noticeable when the user takes part in the process. The complexity of all these processes reveals the need of more flexibility in the communication among agents and between agents and the user [32, 33]. For this purpose, several approaches related to mechanisms to introduce and handle flexible information through linguistic information have been proposed both at levels of agents and users [6, 7, 31]. In such approaches as the user queries as the relevance degrees of retrieved documents are assessed using the same linguistic labels with the same semantics. However, it is obvious that both concepts are different and have a different interpretation. Therefore, it seems reasonable and necessary to assess them with different linguistic label sets, i.e., by using multi-granular linguistic assessments [11].

In this paper we present a distributed intelligent agent model for gathering information on the Internet where the communication among the agents of different levels and among the agents and users is carried out by using a multi-granular linguistic modelling. We assume that in the agent system the user queries, the satisfaction degrees of user queries, and the relevance degrees of retrieved documents are assessed using different linguistic domains or label sets with different granularity. To do so, we use hierarchical linguistic contexts [14] based on the linguistic 2-tuple computational model [12] as representation base of the multi-granular linguistic information. In such a way, we achieve the following advantages: i) the retrieval process is endowed with a higher flexibility, ii) the expressiveness of agent system in the system-user interaction is improved and iii) the processes of computing with words (CW) are made without loss of information and therefore, with more precision.

This paper is structures as follows. In Section 2 we present a short review of the fuzzy linguistic approach, of the 2-tuple fuzzy linguistic representation model and of the hierarchical linguistic contexts. Section 3 shows the structure of the distributed intelligent agent model which uses the multi-granular linguistic model for information gathering. Section 4 presents an example for illustrating the proposal. Finally some conclusions are pointed out.

2 Linguistic Modelling

In this section we present the tools that allow us to apply the linguistic modelling in the distributed intelligent agent model.

2.1 Fuzzy Linguistic Approach

Many aspects of day-to-day activities are evaluated by means of imprecise and fuzzy qualitative values. As was pointed out in this may be arise for different reasons. There are some situations in which information may be unquantifiable due to its nature, and thus, it can be stated only in linguistic terms (e.g., when evaluating the "comfort" or "design" of a car, terms like "good", "fair", "poor" can be used). In other cases, precise quantitative information cannot be stated because either it is unavailable or the cost for its computation is too high and an "approximate value" can be tolerated (e.g., when evaluating the speed of a car, linguistic terms like "fast", "very fast", "slow" can be used instead of numeric values) [11].

The use of Fuzzy Sets Theory has given very good results for modelling qualitative information [34]. It is a technique that handles fuzzines and represents qualitative aspects as linguistic labels by means of "linguistic variables", that is, variables whose values are not numbers but words or sentences in a natural or artificial language. The linguistic approach is used in different fields, such as for example, "information retrieval" [2, 15, 16], "clinical diagnosis" [5], "decision making" [10], etc.

In any linguistic approach, an important parameter to determinate is the "granularity of uncertainty", i.e., the cardinality of the linguistic term set used to express the information. According to the uncertainty degree that an expert qualifying a phenomenon has on it, the linguistic term set chosen to provide his knowledge will have more or less terms. When different experts have different uncertainty degrees on the phenomenon, then several linguistic term sets with a different granularity of uncertainty are necessary (i.e. multi-granular linguistic information) [11]. Typical values of cardinality used in the linguistic models are odd ones, such as 7 or 9, where the mid term represents an assessment of "approximately 0.5", and with the rest of the terms being placed symmetrically around it [1].

One possibility of generating the linguistic term set consists of directly supplying the term set by considering all terms distributed on a scale on which a total order is defined. For example, a set of seven terms S, could be given as follows:

$$S = \{s_0 = N, s_1 = VL, s_2 = L, s_3 = M, s_4 = H, s_5 = VH, s_6 = P\}.$$

Usually, in these cases, it is required that in the linguistic term set there exist:

1. A negation operator: Neg(s_i) = s_j such that $j = g$-i (g+1 is the cardinality).
2. $s_i \leq s_j \iff i \leq j$. Therefore, there exists a *min* and a *max* operator.

The semantics of the linguistic terms is given by fuzzy numbers defined in the [0,1] interval. A way to characterize a fuzzy number is to use a representation based on parameters of its membership function [1]. The linguistic assessments given by the users are just approximate ones, some authors consider that linear trapezoidal membership functions are good enough to capture the vagueness of such linguistic assessments. The parametric representation is achieved by the 4-tuple (a, b, d, c), where b and d indicate the interval in which the membership value is 1, with a and c indicating the left and right limits of the definition domain of the trapezoidal membership function [1]. A particular case of this type of representation are the linguistic assessments whose membership functions are triangular, i.e., $b = d$, then we represent this type of membership functions by a 3-tuple (a, b, c). An example may be the following (Figure 1) :

$$N = (0, 0, .17) \quad VL = (0, .17, .33) \quad L = (.17, .33, .5)$$
$$M = (.33, .5, .67) \quad H = (.5, .67, .83) \quad VH = (.67, .83, 1) \quad P = (.83, 1, 1).$$

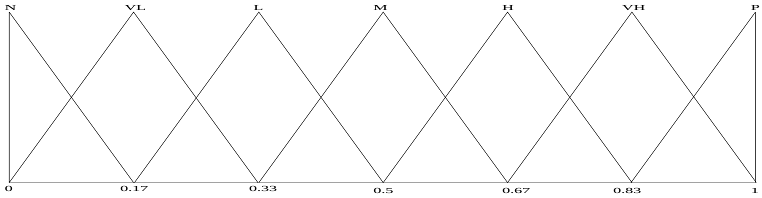

Figure 1: A set of seven linguistic terms with its semantics

2.2 The 2-tuple Fuzzy Linguistic Representation Model Based on the Symbolic Translation

This model and its applications has been presented in [12, 13, 14], showing different advantages of this formalism for representing the linguistic information over classical models, such as:

1. The linguistic domain can be treated as continuous, while in the classical models it is treated as discrete.
2. The linguistic computational model based on linguistic 2-tuples carries out processes of computing with words easily and without loss of information.
3. The results of the processes of computing with words may be always expressed in the initial expression domain.
4. It is possible to aggregate multi-granular linguistic information easily.

Due to these advantages, we shall use this linguistic representation model to accomplish our objective: a higher flexibility, uniformity and precision in the retrieval process with multi-granular information.

2.2.1 The 2-tuple Fuzzy Linguistic Representation Model

Let $S = \{s_0, ..., s_g\}$ be a linguistic term set, if a symbolic method aggregating linguistic information obtains a value $\beta \in [0, g]$, and $\beta \notin \{0, ..., g\}$ then an approximation function ($app_2(\cdot)$) is used to express the index of the result in S.

Definition 1. *Let β be the result of an aggregation of the indexes of a set of labels assessed in a linguistic term set S, i.e., the result of a symbolic aggregation operation. $\beta \in [0, g]$, being $g + 1$ the cardinality of S. Let $i = round(\beta)$ and $\alpha = \beta - i$ be two values, such that, $i \in [0, g]$ and $\alpha \in [-.5, .5)$ then α is called a Symbolic Translation.*

From this concept we shall develop a linguistic representation model which represents the linguistic information by means of 2-tuples (s_i, α_i), $s_i \in S$ and $\alpha_i \in [-.5, .5)$:

- s_i represents the linguistic label of the information, and
- α_i is a numerical value expressing the value of the translation from the original result β to the closest index label, i, in the linguistic term set (s_i), i.e., the Symbolic Translation.

This model defines a set of transformation functions between numeric values and 2-tuples.

Definition 2. *Let $S = \{s_0, ..., s_g\}$ be a linguistic term set and $\beta \in [0, g]$ a value representing the result of a symbolic aggregation operation, then the 2-tuple that expresses the equivalent information to β is obtained with the following function:*

$$\Delta : [0, g] \longrightarrow S \times [-0.5, 0.5)$$

$$\Delta(\beta) = (s_i, \alpha), \; with \; \begin{cases} s_i & i = round(\beta) \\ \alpha = \beta - i & \alpha \in [-.5, .5) \end{cases}$$

where $round(\cdot)$ is the usual round *operation, s_i has the closest index label to "β" and "α" is the value of the symbolic translation.*

Proposition 1. *Let $S = \{s_0, ..., s_g\}$ be a linguistic term set and (s_i, α) be a 2-tuple. There is always a Δ^{-1} function, such that, from a 2-tuple it returns its equivalent numerical value $\beta \in [0, g] \subset \mathcal{R}$.*

Proof.

It is trivial, we consider the following function:

$$\Delta^{-1} : S \times [-.5, .5) \longrightarrow [0, g]$$

$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$$

2.2.2 Linguistic Computational Model Based on Linguistic 2-tuples

In this subsection, we present a computational technique to operate with the 2-tuples without loss of information. We shall present the following computations and operators:

1. Comparison of 2-tuples

The comparison of linguistic information represented by 2-tuples is carried out according to an ordinary lexicographic order.

Let (s_k, α_1) and (s_l, α_2) be two 2-tuples, with each one representing a counting of information:

- if $k < l$ then (s_k, α_1) is smaller than (s_l, α_2)
- if $k = l$ then
  1. if $\alpha_1 = \alpha_2$ then (s_k, α_1), (s_l, α_2) represents the same information
  2. if $\alpha_1 < \alpha_2$ then (s_k, α_1) is smaller than (s_l, α_2)
  3. if $\alpha_1 > \alpha_2$ then (s_k, α_1) is bigger than (s_l, α_2)

2. Negation operator of a 2-tuple

We define the negation operator over 2-tuples as:

$$Neg((s_i, \alpha)) = \Delta(g - (\Delta^{-1}(s_i, \alpha)))$$

where $g + 1$ is the cardinality of S, $S = \{s_0, ..., s_g\}$.

3. Aggregation of 2-tuples

The aggregation of information consists of obtaining a value that summarizes a set of values, therefore, the result of the aggregation of a set of 2-tuples must be a 2-tuple. In the literature we can find many aggregation operators [29] which allow us to combine the information according to different criteria. The fuzzy linguistic representation model with 2-tuples has defined the functions Δ and Δ^{-1} that transform numerical values into 2-tuples and viceversa without loss of information, therefore any numerical aggregation operator can be easily extended for dealing with linguistic 2-tuples [12]. As example of linguistic 2-tuple aggregation operator we shall show the Linguistic Weighted Average operator.

Definition 3 [12]. *Let $x = \{(r_1, \alpha_1), \ldots, (r_n, \alpha_n)\}$ be a set of 2-tuples and $W = \{(w_1, \alpha_1^w), ..., (w_n, \alpha_n^w)\}$ be their linguistic 2-tuple associated weights. The 2-tuple linguistic weighted average $\overline{x}_l^w$ is:*

$$\overline{x}_l^w([(r_1,\alpha_1),(w_1,\alpha_1^w)]...[(r_n,\alpha_n),(w_n,\alpha_n^w)]) = \Delta(\frac{\sum_{t=1}^k \beta_i \cdot \beta_{W_i}}{\sum_{i=1}^n \beta_{W_i}}),$$

with $\beta_i = \Delta^{-1}((r_i,\alpha_i))$ *and* $\beta_{W_i} = \Delta^{-1}(w_i,\alpha_i^w))$.

2.3 Linguistic Hierarchies

The *linguistic hierarchies* are a concept introduced in [4] for the design of *Hierarchical Systems of Linguistic Rules*. The hierarchical linguistic structure was also used in [14] to improve the precision in the processes of CW in linguistic multi-granular contexts.

A *linguistic hierarchy* is a set of levels, where each level is a linguistic term set with different granularity from the remaining of levels of the hierarchy. Each level belonging to a linguistic hierarchy is denoted as $\mathbf{l(t,n(t))}$, being:

1. t, a number that indicates the level of the hierarchy,
2. *n(t)*, the granularity of the linguistic term set of the level t.

Here, we must point out that linguistic hierarchies deal with linguistic terms whose membership functions are triangular-shaped, symmetrical and uniformly distributed in $[0,1]$. In addition, the linguistic term sets have an odd value of granularity representing the central label the value of *indifference*.

The levels belonging to a linguistic hierarchy are ordered according to their granularity, i.e., for two consecutive levels t and $t+1$, $n(t+1) > n(t)$. This provides a linguistic refinement of the previous level.

From the above concepts, we shall define a linguistic hierarchy, LH, as the union of all levels t:

$$LH = \bigcup_t l(t, n(t))$$

To build a linguistic hierarchy we must keep in mind that the hierarchical order is given by the increase of the granularity of the linguistic term sets in each level. Starting from a linguistic term set, S, over the universe of the discourse U in the level t:

$$S = \{s_0, ..., s_{n(t)-1}\}$$

being $s_k, (k = 0, ..., n(t)-1)$ a linguistic term of S.

We extend the definition of S to a set of linguistic term sets, $S^{n(t)}$, each term set belongs to a level t of the hierarchy and has a granularity of uncertainty $n(t)$:

$$S^{n(t)} = \{s_0^{n(t)}, ..., s_{n(t)-1}^{n(t)}\}$$

The building of a linguistic hierarchy satisfies the following rules, that we call, *linguistic hierarchy basic rules*:

1. To preserve all *former modal points* of the membership functions of each linguistic term from one level to the following one.
2. To make *smooth transitions between successive levels*. The aim is to build a new linguistic term set, $S^{n(t+1)}$. A new linguistic term will be added between each pair of terms belonging to the term set of the previous level t. To carry out this insertion, we shall reduce the support of the linguistic labels in order to keep place for the new one located in the middle of them.

Generically, we can say that the linguistic term set of level $t+1$ is obtained from its predecessor t as:

$$l(t, n(t)) \rightarrow l(t+1, 2 \cdot n(t) - 1) \tag{1}$$

Remark: Therefore we can say, that each label of the *level* t is a generating label of two labels in the next level, $t+1$ (excepting the central label).

Table 1 shows the granularity needed in each linguistic term set of the level t depending on the value $n(t)$ defined in the first level (3 and 7 respectively).

Table 1: Linguistic Hierarchies

	Level 1	*Level* 2	*Level* 3
$l(t,n(t))$	$l(1,3)$	$l(2,5)$	$l(3,9)$
$l(t,n(t))$	$l(1,7)$	$l(2,13)$	

A graphical example of a linguistic hierarchy is shown in figure 2:

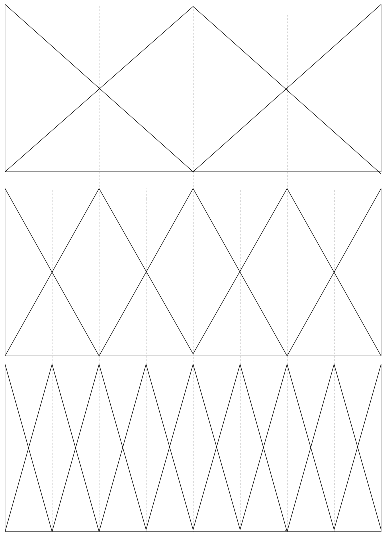

Figure 2: Linguistic Hierarchy of 3, 5 and 9 labels

In [14] were defined transformation functions between labels from different levels to make processes of CW in multi-granular linguistic contexts without loss of information that will be useful in the intelligent agent model under multi-granular linguistic information.

Definition 4. *Let $LH = \bigcup_t l(t, n(t))$ be a linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \{s_0^{n(t)}, ..., s_{n(t)-1}^{n(t)}\}$, and let us consider the 2-tuple linguistic representation. The transformation function from a linguistic label in level t to a label in consecutive level t+c, with $c \in -1, 1$, is defined as:*

$$TF_{t+c}^{t} : l(t, n(t)) \longrightarrow l(t+c, n(t+c)) \tag{2}$$

$$TF_{t+c}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}) \cdot (n(t+c) - 1)}{n(t) - 1})$$

This transformation function was generalized to transform linguistic terms between any linguistic level in the linguistic hierarchy.

Definition 5. *Let $LH = \bigcup_t l(t, n(t))$ be a linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \{s_0^{n(t)}, ..., s_{n(t)-1}^{n(t)}\}$. The recursive transformation function between a linguistic label that belongs to level t and a label in level t'=t+a, with $a \in Z$, is defined as:*

$$TF_{t'}^{t} : l(t, n(t)) \longrightarrow l(t', n(t'))$$

$$
\begin{array}{l}
If\ |a| > 1\ then \\
TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = TF_{t'}^{t+\frac{t-t'}{|t-t'|}}(TF_{t+\frac{t-t'}{|t-t'|}}^{t}(s_i^{n(t)}, \alpha^{n(t)})) \\
\\
If\ |a| = 1\ then \\
TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = TF_{t+\frac{t-t'}{|t-t'|}}^{t}(s_i^{n(t)}, \alpha^{n(t)})
\end{array}
\tag{3}
$$

This recursive transformation function can be easily defined in a non recursive way as follows:

$$TF_{t'}^{t} : l(t, n(t)) \longrightarrow l(t', n(t'))$$

$$TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}) \cdot (n(t') - 1)}{n(t) - 1}) \tag{4}$$

Proposition 2. *The transformation function between linguistic terms in different levels of the linguistic hierarchy is bijective:*

$$TF_{t}^{t'}(TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)})) = (s_i^{n(t)}, \alpha^{n(t)}) \tag{5}$$

This result guarantees the transformations between levels of a linguistic hierarchy are carried out without loss of information.

3 A Distributed Intelligent Agent Model for Information Gathering in Multi-Granular Linguistic Contexts

In this section we present a linguistic agent model for gathering information on the Internet where the communication among the agents of different levels and between users and agents is carried out by using different label sets (multi-granular linguistic information) in order to allow a higher flexibility in the processes of communication of the system. We assume that in the agent system the importance degrees associated with the weighted user queries, the satisfaction degrees of weighted user queries and the relevance degree of the retrieved documents are expressed by means of linguistic values assessed in linguistic term sets with different granularity.

In the first subsection, the main notions of the concept *Intelligent agent* is set, in the second one an architecture for information gathering with these agents is proposed and finally, the process of information gathering that allows to manage the multi-granular linguistic communication in the distributed agent model is given.

3.1 Concept of Intelligent Software Agent

The intelligent software agents have been defined several times in the literature [22, 25, 28]. We are not to give a new definition of this concept, neither to review the ones given previously, but to set the main notions about those characteristics from every of these terms related to our specific purpose.

The concept of *agent* or rather *autonomous agent* must be the first one to be explained. This term, is strongly associated with the "behavior-based AI", as opposed to the "knowledge-based AI" [22], led by the expert systems. As Maes defines in [22], an agent is a system that tries to achieve some predefined goals in a complex and dynamic environment. Thus, depending on the environment, we can set the first big gap, by splitting the concept of agent in those called typically "robots", whose environment is basically physical, and those called "software agents", that inhabit in an environment consisting of computers and networks. Both concepts share one main characteristic: they are autonomous, i.e. they are able to operate and decide themselves the way to achieve their goals. However, as this feature is supposed to be inherent in an agent, an *autonomous agent* is usually called simply *agent*. As for the term *intelligent*, there are several discussions [25] about to consider whether an agent is intelligent by nature or not. We shall consider them as intelligent, since they present, in some sense, human behavior reducing the heaviest work of Internet users. Hence, the agents which with we are dealing with, are *intelligent agents*.

3.2 A Distributed Multi-Agent Architecture on the Internet

Most the designed intelligent agents nowadays are closely connected to the Internet. These agents do not only retrieve and filter information (in the sense of Web documents) [23], but also hand electronic mail, news lists, FAQ lists, ..., [19, 21, 28]. These are properly called *interface agents* [21], since they are more closely to the user. However, all the information that these agents get, come from somewhere or somewhat. There are servers through the Internet that proportionate these services of information, mail, news and FAQs. The agents closest to these data sources are called *information agents* [27]. Since Internet users can access to their interface or personal agents, as well as the general information agents, they feel completely lost and overloaded of information due to this avalanche of agents. This problem reveals the need of an organisation among the agents within Internet that implies both an agent hierarchy and architecture. Since the disposition of the elements taking part in the retrieval information process is distributed, it seems sensible to consider the architecture as a distributed one. Several architectures for these multi-agents distributed models have been proposed and reviewed [20, 24, 27, 28]. However, the architecture that fits better to our model is the one proposed by Sycara et al. in [27]. In this architecture, besides the aforementioned *interface* and *information agents*, the authors consider a third type of agents, the *task agents*. These agents deal with the decision-making process and the exchange of information with the information agents, resolving conflicts and fusing information, in order to release the interface agents of some tasks that make them ineffective.

A hierarchical model with five levels is proposed, as set out below:

- **Level 1:** *Internet Users*, which look for Web documents on the Internet by means of a weighted query where a set of terms related to the desired documents is specified.
- **Level 2:** *Interface Agents* (one for user, generally), that communicate the user's weighted query to the task agents, and filter the retrieved documents from task agents in order to give to the users those that satisfy better their needs.
- **Level 3:** *Task Agents* (one for interface agent, generally), that communicate the user's query to the information agents, and get those documents from every information agent that fulfills better the query, fusing them and resolving the possible conflicts among the information agents.
- **Level 4:** *Information Agents*, which receive the weighted query from the task agents, look for the information in the data sources, and give the retrieval documents back to the previous level.
- **Level 5:** *Information Sources*, consisting of all data sources within the Internet, such as databases and information repositories.

The scheme of this model can be observed in Figure 3.

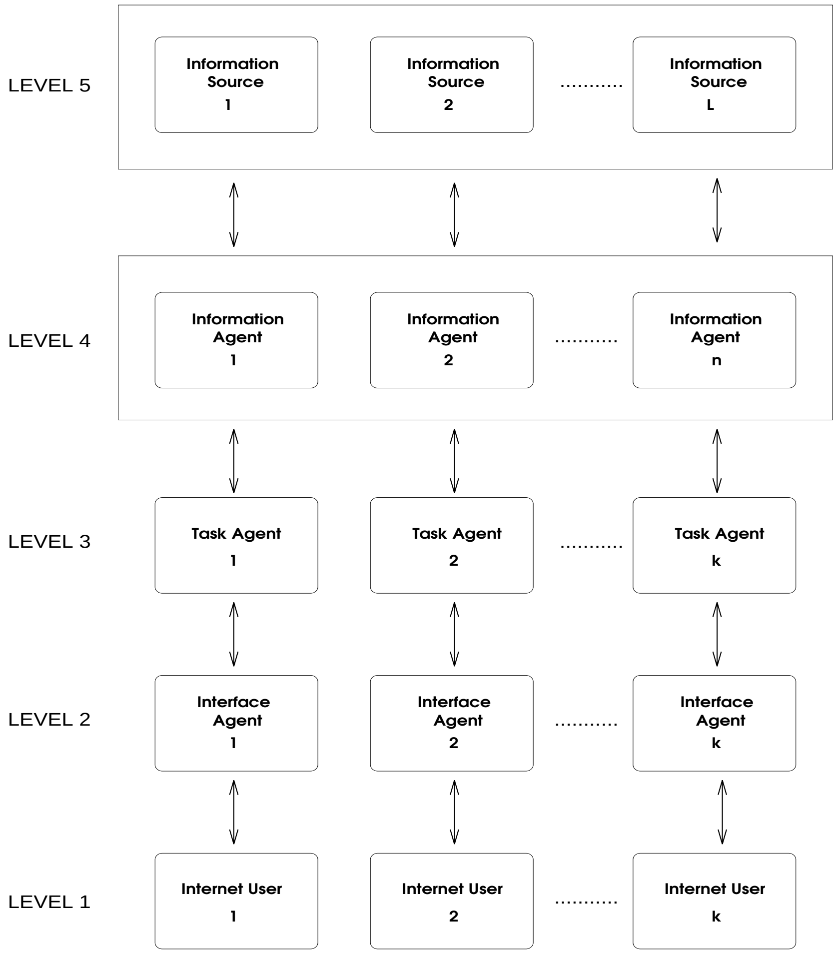

Figure 3: A General Overview of the Distributed Intelligent Agent Model

3.3 Information Gathering By a Multi-Granular Linguistic Distributed Intelligent Agent Model

In the process of information gathering, as a response of a weighted user query on the presented agent model, there are two different parts:

- On the one hand, there is a communication between agents at levels 5-4 and 4-3, which is far from the user's participation, and where the question to be decided by the task agent is about which information agents would satisfy better the user's needs.
- On the other hand, there is a communication between agents at levels 3-2 and the user, where the information element is specifically the set of retrieved documents that will be analyzed and filtered by the interface agents.

In [6, 7] we present some linguistic approaches to incorporate more flexibility in the communication carried out in the process of information gathering. The problem is that we always use the same linguistic domain to express the different assessments (importance degrees associated with the user queries, satisfaction degrees of user queries and relevance degrees of the retrieved documents) that appear in the communication process.

In this paper we overcome the above problem by allowing that the different assessments of communication process can be assessed on different linguistic domains, i.e., by using multi-granular linguistic information. To do so, we propose that the system deals with a linguistic hierarchy $LH = \bigcup_t l(t, n(t))$, to express the different assessments, by using a level to assess each kind of assessment. For example, assuming the linguistic hierarchy shown in the Figure 2, the users can assess the importance degrees associated with the queries in the first level, the agents can assess the satisfaction degrees of a query in the second one and the relevance degrees of the retrieved documents in the third one.

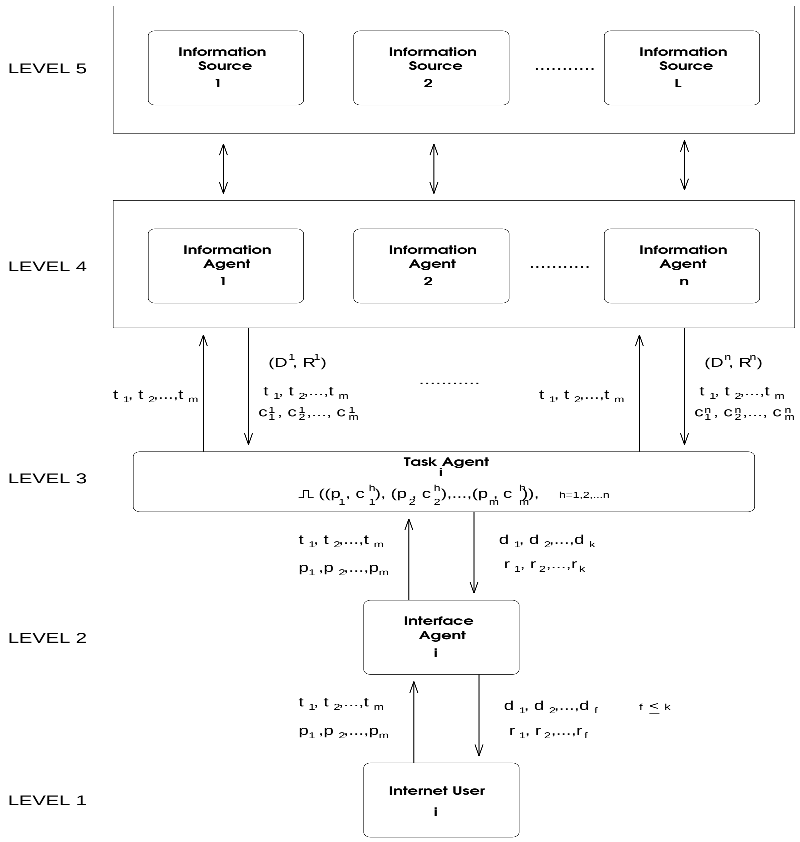

Figure 4: An Overview of Information Flows in a Single User Scheme

Then, the description of the information gathering process related to a single user (see Figure 4) in a multi-granular linguistic context is as follows:

- **Step 1:** An *Internet user* makes a query to look for those documents related to the terms $\{t_1,\ t_2,\ ...,\ t_m\}$, which are weighted by a linguistic degree of importance $\{p_1,\ p_2,\ ...,\ p_m\},\ p_i \in S^3$. Both set of values are given by the user to the *interface agent*.

- **Step 2:** The *interface agent* gives the terms and their importance weights to the *task agent*.

- **Step 3:** The *task agent* makes the query to all the information agents to which it is connected, and give them the terms $\{t_1,\ t_2,\ ...,\ t_m\}$.

- **Step 4:** All the *information agents* that have received the query, look for the information that better satisfies it in the information sources, and retrieve from them the documents.

- **Step 5:** The *task agent* receives from every *information agent* h a set of documents and their relevances (D^h, R^h) ordered decreasingly by relevance [26], where every document d_j^h has an associated linguistic degree of relevance $r_j^h \in S^9$ $(j = 1, ..., card(D^h))$ assessed in the set with maximum granularity of the linguistic hierarchy. It also receives a linguistic degree of satisfaction [2] $c_1^h,\ c_2^h, ..., c_m^h,\ c_i^h \in S^5$ (whose equivalent 2-tuples are $(c_1^h, 0),\ (c_2^h, 0), ..., (c_m^h, 0)$) of this set of documents with regard to every term of the query.

  – **Step 5.1:** The *task agent* aggregates both linguistic information weights, the satisfactions of the terms of the query from every *information agent*, $(c_i^h, \alpha), c_i^h \in S^5$, and the importance weights that the user assigned to these terms, $(p_i, \alpha), p_i \in S^3$, using the aggregation process for multi-granular linguistic information presented in [14]:

    1. *Normalization Phase*: the linguistic term set with highest granularity of the linguistic multi-granular context is chosen to make uniform the multi-granular linguistic information. Then, all the information are expressed in that linguistic term set by means of 2-tuples.
    2. *Aggregation Phase*: through a 2-tuple aggregation operator the information is aggregated. In this paper we use the 2-tuple linguistic weighted average operator, $\overline{x}_l^w$, for combining the satisfactions of the terms of the query and the importance weights.

    Let $\{[(p_1, \alpha), (c_1^h, \alpha)],\ ..., [(p_m, \alpha), (c_m^h, \alpha)]\},\ p_i \in S^3 \ and\ c_i^h \in S^5$ be the set of pairs of linguistic 2-tuples of importance and satisfaction to be aggregated by the task agent for every information agent h. Then, for combining them first the linguistic values $(p_i, \alpha), p_i \in S^3$ and $(c_m^h, \alpha), c_m^h \in S^5$ are transformed in the linguistic term set with maximum granularity in the Linguistic Hierarchy, in this case S^9, obtaining their corresponding values $(\overline{p_i}, \alpha), \overline{p_i} \in S^9$ and $(\overline{c_m^h}, \alpha), \overline{c_m^h} \in S^9$. Once the multi-granular information has been unified according to the 2-tuple linguistic weighted average operator definition, the aggregation of the pair associated with every term is obtained as:

    $$\lambda^h = \overline{x}_l^w([(\overline{p_1}, \alpha), (\overline{c_1^h}, \alpha)],\ ..., [(\overline{p_m}, \alpha), (\overline{c_m^h}, \alpha)])$$

  – **Step 5.2:** Once the *task agent* has calculated the overall performances $\{\lambda^1,\ ..., \lambda^n\}$, $\lambda^j \in S \times [-.5, .5)$ of the *n information agents* through the aggregation operator, it must decide which agent fulfil better the user's query. For this purpose, the task agent orders the performances decreasingly and obtains the vector $\{\Theta_1,\ ..., \Theta_n\}$, $\Theta_j \in S \times [-.5, .5)$ as follows:

    $$\{\Theta_1,\ ..., \Theta_n\} = \sigma(\{\lambda^1,\ ..., \lambda^n\}) = \{\lambda^{\sigma(1)},\ ..., \lambda^{\sigma(n)}\},$$

    where σ is a permutation over the set of linguistic 2-tuples $\{\lambda^1,\ ..., \lambda^n\}$ and

    $$\lambda^{\sigma(j)} \leq \lambda^{\sigma(i)}\ \forall i \leq j.$$

    In order to gather the better documents, the task agent may decide on two alternatives.

    * The first one is the selection of the information agent with the higher satisfaction of the query, Θ_1. This alternative presents a main drawback, as the set of documents of the selected agent contains some documents that, probably, will be less relevant to the query than some of the best documents of the rest of the information agents. This problem leads us to the second alternative, based on the selection of the best documents of every agent.

$*$ In the second one, with the purpose of selecting a number of documents from every agent being proportional to the degree of satisfaction of such an agent:

$$P_s(\Theta_h) = \frac{\Delta^{-1}(\lambda^h)}{\sum_{i=1}^{n} \Delta^{-1}(\lambda^i)}$$

Finally, the number of documents, $k(D^h)$, that the *task agent* would select from such an agent is expressed as:

$$k(D^h) = round(\frac{\sum_{i=1}^{n} card(D^i)}{n} \cdot P_s(\Theta_h)).$$

- **Step 6:** The *interface agent* receives from the *task agent* an ordered list of documents and their relevances $\{(d_j^h, r_j^h)\}$, where $d_j^h \in D^h$, $r_j^h \in R^h$, $1 \leq h \leq n$ and $j = 1, ..., k(D^h)$.

- **Step 7:** The *interface agent* filters these documents in order to give to the user only those documents that fulfill better his/her needs.

4 Example

In the following, an example of the application through this architecture is explained, using the Linguistic Hierarchy shown in Figure 2 whose terms in each level are:

$S^3 = \{a_0, a_1, a_2\}$
$S^5 = \{b_0, b_1, b_2, b_3, b_4\}$
$S^9 = \{c_0, c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8\}$

For this purpose, a view of a single user i will be considered, as it was set out in Figure 4. In this example, we will consider four information agents. Let us suppose an user making a query to Internet through an interface agent at the lowest levels of the presented architecture. The user may be interested in 'Agents', and more specifically, in 'Information Agents', to which the terms 'Agents' and 'Information' may be introduced as terms in the query. These terms may be weighted by means of linguistic 2-tuples related to importance. In order to simplify the task of the user to evaluate the documents using linguistic terms in S^3:

$$S^3 = \{a_0, a_1, a_2\}$$

where $a_2 > a_1 > a_0$. Since the user is quite interested in the topic 'Agents' and, explicitly, in 'Information Agents', the labels associated to the query terms may be a_2 for the term 'Agents', and a_1 for the term 'Information'.

Therefore, the parameters which the user will communicate to the interface agent would be as follows:

$$(t_1, (p_1, \alpha)) = ('Agents', (a_2, 0)) \quad (t_2, (p_2, \alpha)) = ('Information', (a_1, 0))$$

The interface agent will go through the task agent, which will merely pass the terms of the query to the information agent level. The information agents search in the information source level those documents related to the terms of the query, and get a list with the most relevant links [2, 15]. For instance, each information agent h ($h = 1, \ldots, 4$) may retrieve a set of five links, D^h and their relevances R^h where each relevance degree r_j^h is assessed in S^9 (see Table 1).

(D^h, R^h)	d_j^h	r_j^h
(D^1, R^1)	http://phonebk.duke.edu/clients/tnfagent.html	c_6
	http://webhound.www.media.mit.edu/projects/webhound/doc/Webhound.html	c_6
	http://www.elet.polimi.it/section/compeng/air/agents/	c_5
	http://www.cs.bham.ac.uk/ámw/agents/links/	c_4
	http://groucho.gsfc.nasa.gov/Code_520/Code_522/Projects/Agents/	c_3
(D^2, R^2)	http://lcs.www.media.mit.edu/people/lieber/Lieberary/Letizia/Letizia.html	c_8
	http://www.osf.org/ri/contracts/6.Rationale.frame.html	c_7
	http://www.info.unicaen.fr/ serge/sma.html	c_7
	http://www.cs.umbc.edu/ cikm/1994/iia/papers/jain.html	c_3
	http://www.hinet.com/realty/edge/gallery.html	c_0
(D^3, R^3)	http://activist.gpl,ibm.com/WhitePaper/ptc2.htm	c_8
	http://www.cs.umbc.edu/ cikm/iia/submitted/viewing/chen.html	c_5
	http://www.psychology.nottingham.ac.uk:80/aigr/research/agents/agents.html	c_5
	http://netq.rowland.org/isab/isab.html	c_4
	http://maple.net/gbd/salagnts.html	c_3
(D^4, R^4)	http://www.ncsa.uiuc.edu/SDG/IT94/Proceedings/Agents/spetka/spetka.html	c_8
	http://mmm.wiwi.hu-berlin.de/MMM/cebit_engl.html	c_5
	http://foner.www.media.mit.edu/people/foner/Julia/subsection3_2_2.html	c_3
	http://www.cs.bham.ac.uk/ mw/agents/index.html	c_3
	http://www.ffly.com/html/About1.html	c_1

Table 1: Sets of Documents for the Terms 'Agents' and 'Information'

Each information agent h gives back to the task agent a set with the degree of relevance and the linguistic degree of satisfaction $c_i^h \in S^5$ of the set D^h with regard to every term p_i of the query, according to the following:

$$\begin{array}{rl}
[(c_1^1, \alpha), (c_2^1, \alpha)] = & [(b_2,0),\ (b_1,0)] \\
[(c_1^2, \alpha), (c_2^2, \alpha)] = & [(b_3,0),\ (b_3,0)] \\
[(c_1^3, \alpha), (c_2^3, \alpha)] = & [(b_3,0),\ (b_2,0)] \\
[(c_1^4, \alpha), (c_2^4, \alpha)] = & [(b_3,0),\ (b_1,0)]
\end{array}$$

Once the task agent has received this information from the previous level, it aggregates both the satisfaction degrees and the importance degrees which had been obtained through the internet agent in an earlier step. To do so, it makes the information uniform in the term set with maximum granularity, S^9. Hence, the pairs of importance and satisfaction are aggregated by the task agent for every information agent h:

$$\begin{array}{rl}
([(\overline{p_1}, \alpha), (\overline{c_1^1}, \alpha)], [(\overline{p_2}, \alpha), (\overline{c_2^1}, \alpha)]) = & ([(c_8,0),\ (c_4,0)],[(c_4,0),\ (c_2,0)]) \\
([(\overline{p_1}, \alpha), (\overline{c_1^2}, \alpha)], [(\overline{p_2}, \alpha), (\overline{c_2^2}, \alpha)]) = & ([(c_8,0),\ (c_6,0)],[(c_4,0),\ (c_6,0)]) \\
([(\overline{p_1}, \alpha), (\overline{c_1^3}, \alpha)], [(\overline{p_2}, \alpha), (\overline{c_2^3}, \alpha)]) = & ([(c_8,0),\ (c_6,0)],[(c_4,0),\ (c_4,0)]) \\
([(\overline{p_1}, \alpha), (\overline{c_1^4}, \alpha)], [(\overline{p_2}, \alpha), (\overline{c_2^4}, \alpha)]) = & ([(c_8,0),\ (c_6,0)],[(c_4,0),\ (c_2,0)])
\end{array}$$

The aggregation of each pair is carried out through the 2-tuple linguistic weighted average, $\overline{x}_l^w$. Therefore, the overall fulfillment λ^h of the information agent h will be determined by the following expressions:

$$\begin{array}{c}
\lambda^1 = \overline{x}_l^w([(c_8, 0), (c_4, 0)], [(c_4, 0), (c_2, 0)]) = (\mathbf{c_3}, \mathbf{.33}) \\
\lambda^2 = \overline{x}_l^w([(c_8, 0), (c_6, 0)], [(c_4, 0), (c_6, 0)]) = (\mathbf{c_6}, \mathbf{0}) \\
\lambda^3 = \overline{x}_l^w([(c_8, 0), (c_6, 0)], [(c_4, 0), (c_4, 0)]) = (\mathbf{c_5}, \mathbf{.33}) \\
\lambda^4 = \overline{x}_l^w([(c_8, 0), (c_6, 0)], [(c_4, 0), (c_2, 0)]) = (\mathbf{c_5}, -\mathbf{.33})
\end{array}$$

Hence, the overall performances of the information agents is:

$$\{\lambda^1, \lambda^2, \lambda^3, \lambda^4\} = \{(c_3, .33), (c_6, 0), (c_5, .33), (c_5, -.33)\}$$

In the next step,the task agent would order these values decreasingly as follows:

$$\{\Theta_1, \Theta_2, \Theta_3, \Theta_4\} = \{\lambda^2, \lambda^3, \lambda^4, \lambda^1\} = \{(c_6, 0), (c_5, .33), (c_5, -.33), (c_3, .33)\}$$

As it was explained in Section 3.3 (step 5.2), the task agent may decide on choosing the information agent with the highest performance, or select the best documents from all the agents, according to the performance of each one. In general, this last solution is most suitable when all the information agents present similar performances, as it is our case. Therefore, the task agent will calculate the probabilities of selection of the documents of each agent, according to the scheme of selection probabilities referenced in Step 5.2, which expression would set as follows:

$$P_s(\Theta_h) = \frac{\Delta^{-1}(\lambda^h)}{\sum_1^4 \Delta^{-1}(\lambda^i)},$$

Obtaining,

$$P_s(\Theta_1) = 0.137, P_s(\Theta_2) = 0.310, P_s(\Theta_3) = 0.276 \text{ and } P_s(\Theta_4) = 0.241.$$

Finally, the task agent would calculate the number of documents $k(D^h), h = 1, \ldots, n$ to select from each agent. The result of this computation would be:

$$k(D^1) = 1, k(D^2) = 2, k(D^3) = 1, k(D^4) = 1.$$

Hence, the final list of documents ordered by relevance that the interface agent would receive from the task agent would be:

$(d_1^2, r_1^2) =$ *(http://lcs.www.media.mit.edu/people/lieber/Lieberary/Letizia/Letizia.html,* c_8*)*
$(d_1^3, r_1^3) =$ *(http://www.activist.gpl.ibm.com/WhitePaper/ptc2.htm,* c_8*)*
$(d_1^4, r_1^4) =$ *(http://www.ncsa.uiuc.edu/SDG/IT94/Proceedings/Agents/spetka/spetka.html,* c_8*)*
$(d_2^2, r_2^2) =$ *(http://www.osf.org/ri/contracts/6.Rationale.frame.html,* c_7*)*
$(d_1^1, r_1^1) =$ *(http://phonebk.duke.edu/clients/tnfagent.html,* c_6*)*

In the last step of the information gathering process, the interface agent would filter this final ranked list of documents and would give to the user the most relevant documents.

This information gathering process guarantees that the user will receive the most relevant documents for his/her query, due to the fact, in step 5.2 we have chosen the second alternative proposed in the algorithm. Therefore, the ranking list of documents given to the user contains the documents with highest degree of satisfaction (to the query) according to all the agents avoiding a biassed selection of documents.

5 Concluding Remarks

We have presented a distributed intelligent agent system where the communication processes carried out in the information gathering are modelled by means of the multi-granular linguistic information. To do so, we have used the hierarchical linguistic contexts and the 2-tuple linguistic computational model.

We may stand out two main advantages of this proposal:

- The use of the multi-granular linguistic information allows a higher flexibility and expressiveness in the communication among the agents and users and agents in the information gathering process.
- The use of the multi-granular linguistic information does not decrease the precision of system in its results.

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