Improving the User-System Interaction in a Web Multi-agent System Using Fuzzy Multi-granular Linguistic Information

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Abstract. Nowadays, information gathering in Internet is a complex activity and Internet users need systems to assist them to obtain the information required. In an earlier studies [5, 6, 16] we presented different fuzzy linguistic multi-agent models for helping users in their information gathering processes on the Web. In this paper, we present a new fuzzy linguistic multi-agent model to access information on the Web that incorporates the use of fuzzy multi-granular linguistic modeling to improve its user-system interaction and be more user-friendly.

Keywords: Web, intelligent agents, fuzzy linguistic modelling.

1 Introduction

Information gathering on Internet is a very important, widely studied and hotly debated topic. One of the central problems in Internet is the growth of information to which Internet users are exposed. The exponential increase of 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. Users are in need of systems to help them cope with the large amount of information available on the Web [2, 18, 21, 22]. Examples of such systems include Web search engines, meta-search engines, multi-agent systems and information filtering systems [1].

A multi-agent system is one in which a number of agents cooperates and interact with each other in a distributed environment. On the Web the activity of a multi-agent system 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. In a typical multi-agent system, the agents work together to achieve a global objective based on distributed data and control. Multi-agent systems have been widely used in Web applications [23, 25]. In the activity of a multi-agent system a basic aspect is an efficient communication among agents. The great variety of representations of the information in Internet

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is the main obstacle to this communication, and the problem becomes more noticeable when users take part in the process. This reveals the need of more flexibility in the communication among agents and between agents and users [5, 29, 30]. To solve this problem we have applied satisfactorily the fuzzy linguistic approach [8, 9, 11, 31] in the development of different models of distributed multi-agent systems [5, 6, 16]. In these models the communication processes are improved by representing the information by means of linguistic labels. The drawback is that as the user queries as the relevance degrees of retrieved documents are assessed using the same linguistic label set with the same semantics. However, both concepts are different and have a different interpretation, and therefore, it seems reasonable and necessary to assess them with different linguistic label sets, i.e., by using multi-granular linguistic assessments [12, 15].

The aim of this paper is to present a new model of Web multi-agent system to access and retrieve information on the Web that incorporates in its activity the use of fuzzy multi-granular linguistic information to improve the user-system interaction. The communication among the agents of different levels and among the agents and users is carried out by using fuzzy multi-granular linguistic information, i.e., the different types of information that participate in the activity of the Web multi-agent system (query weights, user satisfaction degrees, relevance degrees, recommendations) are assessed with different uncertainty degrees, using several label sets with a different granularity of uncertainty. As in [16] we use the 2-tuple fuzzy linguistic representation [11] to model the linguistic information. To process the multi-granular linguistic information in the Web retrieval context we propose a method based on hierarchical linguistic contexts [12] as representation base of the multi-granular linguistic information. This new Web multi-agent model allows to represent the information in the retrieval processes with different levels of granularity. In such a way, the elements that participate in the retrieval processes are represented better and the user-system interaction is improved.

The rest of the paper is structured as follows. Section 2 reviews the fuzzy multi-granular linguistic modeling. Section 3 presents the new Web multi-agent model, and finally, some concluding remarks are pointed out.

2 Fuzzy Multi-granular Linguistic Modeling

In this section we present the fuzzy multi-granular linguistic modeling used to design the Web multi-agent model. So, we analyze the 2-tuple fuzzy linguistic approach [11], the concept of fuzzy multi-granular linguistic information and the fuzzy linguistic hierarchies [4] used in [12] to represent fuzzy multi-granular linguistic information.

2.1 The 2-Tuple Fuzzy Linguistic Approach

The 2-tuple fuzzy linguistic approach was introduced in [11] to overcome the problems of loss of information of other fuzzy linguistic approaches [8, 9, 10, 31].

Its main advantage is that the linguistic computational model based on linguistic 2-tuples can carry out processes of computing with words easier and without loss of information. To define it we have to establish the 2-tuple representation model and the 2-tuple computational model to represent and aggregate the linguistic information, respectively.

2.1.1 The 2-Tuple Representation Model

Let $S = \{s_0, ..., s_g\}$ be a linguistic term set with odd cardinality ($g + 1$ is the cardinality of S), where the mid term represents an assessment of approximately 0.5 and with the rest of the terms being placed symmetrically around it. We assume that the semantics of labels is given by means of triangular membership functions represented by a 3-tuple (a, b, c) and consider all terms distributed on a scale on which a total order is defined $s_i \leq s_j \Longleftrightarrow i \leq j$.

In this fuzzy linguistic context, if a symbolic method [8, 9, 10] aggregating linguistic information obtains a value $\beta \in [0, g]$, and $\beta \notin \{0, ..., g\}$, then an approximation function is used to express the result in S.

Definition 1. [11] *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, $\beta \in [0, g]$. Let $i = round(\beta)$ ($round(\cdot)$ is the usual* round *operation) 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.*

Roughly speaking, the symbolic translation of a linguistic term, s_i, is a numerical value assessed in $[-.5, .5)$ that supports the "difference of information" between a counting of information $\beta \in [0, g]$ obtained after a symbolic aggregation operation and the closest value in $\{0, ..., g\}$ that indicates the index of the closest linguistic term in S ($i = round(\beta)$).

The 2-tuple representation model is developed from the concept of symbolic translation by representing 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 ($s_i \in S$).

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

Definition 2. [11] *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 function $\Delta : [0, g] \longrightarrow S \times [-0.5, 0.5)$ such that*

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

where s_i has the closest index label to "β" and "α" is the value of the symbolic translation.

In [11] was demonstrated that for Δ there exists Δ^{-1} defined as $\Delta^{-1}(s_i,\alpha) = i+\alpha$, and that the conversion of a linguistic term into a linguistic 2-tuple consists of adding a symbolic translation value of 0: $s_i \in S \Longrightarrow (s_i, 0)$.

2.1.2 2-Tuple Computational Model

The 2-tuple computational model is defined by presenting the comparison of 2-tuples, a negation operator and aggregation operators of 2-tuples.

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) and (s_l, α_2) represent 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 2-tuples. $Neg((s_i, \alpha)) = \Delta(g - (\Delta^{-1}(s_i, \alpha)))$.
3. Aggregation operators 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 which allow us to combine the information according to different criteria. Using functions Δ and Δ^{-1} that transform without loss of information numerical values into linguistic 2-tuples and viceversa, any of the existing aggregation operators can be easily extended for dealing with linguistic 2-tuples. Some examples are:

Definition 3. *Let $x = \{(r_1, \alpha_1), \dots, (r_n, \alpha_n)\}$ be a set of linguistic 2-tuples, the 2-tuple arithmetic mean $\overline{x}^e$ is computed as, $\overline{x}^e[(r_1, \alpha_1), \dots, (r_n, \alpha_n)] =$*
$\Delta(\sum_{i=1}^{n} \frac{1}{n}\Delta^{-1}(r_i, \alpha_i)) = \Delta(\frac{1}{n}\sum_{i=1}^{n} \beta_i)$.

Definition 4. *Let $x = \{(r_1, \alpha_1), \dots, (r_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{w_1, ..., w_n\}$ be their associated weights. The 2-tuple weighted average $\overline{x}^w$ is: $\overline{x}^w[(r_1, \alpha_1), \dots, (r_n, \alpha_n)] = \Delta(\frac{\sum_{i=1}^{n} \Delta^{-1}(r_i,\alpha_i)\cdot w_i}{\sum_{i=1}^{n} w_i}) = \Delta(\frac{\sum_{i=1}^{n} \beta_i \cdot w_i}{\sum_{i=1}^{n} w_i})$.*

Definition 5. *Let $x = \{(r_1, \alpha_1), \dots, (r_n, \alpha_n)\}$ be a set of linguistic 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: $\overline{x}_l^w[((r_1, \alpha_1), (w_1, \alpha_1^w))...((r_n, \alpha_n), (w_n, \alpha_n^w))] = \Delta(\frac{\sum_{i=1}^{n} \beta_i \cdot \beta_{W_i}}{\sum_{i=1}^{n} \beta_{W_i}})$, with $\beta_i = \Delta^{-1}(r_i, \alpha_i)$ and $\beta_{W_i} = \Delta^{-1}(w_i, \alpha_i^w)$.*

2.2 Fuzzy Multi-granular Linguistic Information

In any fuzzy linguistic approach, an important parameter to determinate is the “granularity of uncertainty”, i.e., the cardinality of the linguistic term set S used to express the linguistic 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) [12, 15, 17]. In the latter case, we need tools for the management of fuzzy multi-granular linguistic information.

2.3 Fuzzy Linguistic Hierarchies

A *fuzzy 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 [4]. Each level belonging to a linguistic hierarchy is denoted as *l(t,n(t))*, being t a number that indicates the level of the hierarchy and *n(t)* the granularity of the linguistic term set of the level t.

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

A fuzzy linguistic hierarchy, *LH*, is defined as the union of all levels t: $LH = \bigcup_t l(t, n(t))$. To build LH 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. Let $S^{n(t)} = \{s_0^{n(t)}, ..., s_{n(t)-1}^{n(t)}\}$ be the linguistic term set defined in the level t with $n(t)$ terms, then the building of a fuzzy linguistic hierarchy must satisfy the following fuzzy linguistic hierarchy basic rules [12]:

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 transactions 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*, $S^{n(t+1)}$, is obtained from its predecessor level t, $S^{n(t)}$ as: $l(t, n(t)) \rightarrow l(t+1, 2 \cdot n(t) - 1)$.

Table 1. Fuzzy 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)	

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).

In [12] it was demonstrated that the fuzzy linguistic hierarchies are useful to represent and combine fuzzy multi-granular linguistic information without loss of information. To do this, a family of transformation functions between labels from different levels was defined:

Definition 6. *Let $LH = \bigcup_t l(t, n(t))$ be a fuzzy linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \{s_0^{n(t)}, ..., s_{n(t)-1}^{n(t)}\}$. The transformation function between a 2-tuple that belongs to level t and another 2-tuple in level $t' \neq t$ is defined as:*

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

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

As it was pointed out in [12] this family of transformation functions is bijective.

3 A Web Multi-agent Model Based on Fuzzy Multi-granular Linguistic Information

In this Section we present a new fuzzy linguistic Web multi-agent model that improves the user-system interaction. It is developed from multi-agent model defined in [16] but using in its activity fuzzy multi-granular linguistic information.

As aforementioned, in multi-agent systems an important problem is the design of appropriate communication protocols among the agents, which is more noticeable when users take part in the process. We deal with this problem by using different fuzzy linguistic approaches [8, 9, 11, 31] as a way to introduce and handle flexible information by means of linguistic labels in the communication processes of some multi-agent models [5, 6, 16].

In [16] we presented a Web multi-agent model that combines in its activity the two more important existing filtering techniques, content-based filtering and collaborative filtering [26, 27]. In a search session a user provides his/her information needs by means of a linguistic multi-weighted query and an interest topic. Then, in a first phase the system develops the documentary retrieval using the user query, in a second phase it develops the documentary filtering using the user interest topic, and finally in a third phase it receives the user feedback, i.e., user recommendations on the accessed documents. In the complete retrieval process the linguistic information is represented using the same linguistic term set.

In this paper we present a new Web multi-agent model that could be considered as a refined system of that drawn in [16]. The refinement consists to carry out the communication among the agents of different levels and between users and agents by using different label sets, i.e. working with fuzzy multi-granular linguistic information, in order to allow a higher flexibility in the processes of communication of the system and in such a way, to improve the user-system interaction.

We consider that different assessments of retrieval activity must be assessed on different label sets, i.e., by using fuzzy multi-granular linguistic information. We assume that in the agent system the threshold weights and the relative importance weights associated with the terms of the user queries, the satisfaction degrees of weighted user queries, the relevance degree of the retrieved documents and the recommendations of the documents are expressed by means of linguistic values assessed in linguistic term sets with different granularity, S_1, S_2, S_3, S_4 and S_5 respectively. We use the linguistic term sets represented in fuzzy linguistic hierarchies to express linguistic information. For example, assuming the linguistic hierarchy shown in Table 1, the users can assess the threshold weights in the second level ($S_1 = S^5$), the relative importance weights associated with the terms in a queries in the first one ($S_2 = S^3$), the agents can assess the satisfaction degrees of a query in the second one ($S_3 = S^5$), the relevance degrees of the retrieved documents in the third one ($S_4 = S^9$), and the recommendations expressed by the users in the third one ($S_5 = S^9$).

The new Web multi-agent model presents a architecture with seven levels of activity as in [16] (see Figure 1) but all of them working with multi-granular linguistic information:

Level 1: *Internet user*, which expresses his/her information needs by means of a linguistic multi-weighted query. Each term of a user query can be weighted simultaneously by two linguistic weights. The first weight is associated with a classical threshold semantics and the second one with a relative importance semantics. Then, the 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 threshold $\{p^1_1, p^1_2, ..., p^1_m\}$ with $p^1_i \in S_1$, and by a linguistic degree of relative importance $\{p^2_1, p^2_2, ..., p^2_m\}$ with $p^2_i \in S_2$. All this information is given by the user to the *interface agent*.

Level 2: *Interface agent*(one for user), that communicates the user's weighted query to the task agents, and filters the retrieved documents from task agents in order to give to the users those that satisfy better their needs.

Level 3: *Collaborative filtering agent* (one for interface agent), that communicates the user multi-weighted query to the task agent, receives the more relevant documents chosen by the task agent, retrieves the recommendations on such documents from a collaborative recommendation system using only the recommendations of users with similar profiles to the user that introduce the query ($RC^{\mathcal{A}_i} = \{RC^{\mathcal{A}_i}_1, ..., RC^{\mathcal{A}_i}_v\}$ $RC^{\mathcal{A}_i}_j \in S_5 \times [-0.5, 0.5)$), filters the documents by recalculating their relevance using these recommendations, and communicates these documents together with their new relevance degrees to the interface agent. Later, it carries out the tasks to update in the collaborative recommendation system the recommendations on the documents used by the user, i.e., it invites user to provide a recommendation rc_y on each chosen document $d^U_y \in DU$ and this recommendation is stored in the collaborative recommendation system together with the recommendations provided by other users that used d^U_y.

Level 4: *Task agent* (one for interface agent, generally), that communicate the user's query to the information agents, and get those documents from every

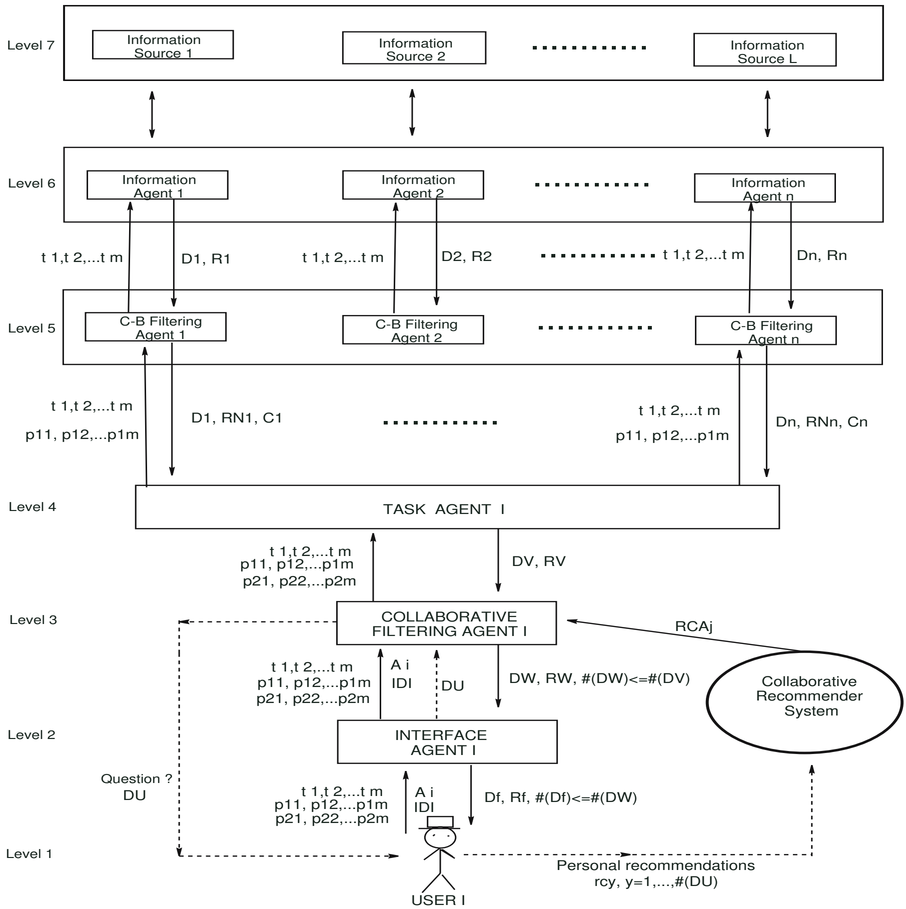

Fig. 1. Structure of a Multi-agent Model Based on Filtering Agents

information agent that fulfills better the query, fusing them and resolving the possible conflicts among the information agents.

Level 5: *Content-based filtering agent* (one for agent information). Each content-based filtering agent communicates the terms of user query to its respective information agent and filters the relevant documents provided by its information agent by recalculating their relevance using the threshold weights. Then, the task agent receives from every content-based filtering agent h a set of documents and their relevance (D^h, RN^h), where every document d_h^h has associated a linguistic degree of relevance expressed in linguistic 2-tuples $rn_j^h \in S_4 \times [-0.5, 0.5)$ $(j = 1, ..., Card(D^h))$. It also receives a set of linguistic degrees of satisfaction $C^h = \{c_1^h, c_2^h, ..., c_m^h\}$, $c_i^h \in S_3 \times [-0.5, 0.5)$ of this set of documents D^h with regard to every term of the query t_i.

Level 6: *Information agents*, which receive the terms of user query from the content-based filtering agents and look for the documents in the information sources. Then, each content-based filtering agent h receives from its respective information sources h the set of relevant documents that it found through information sources D^h and their relevance R^h, where every document d_j^h has an associated degree of relevance $r_j^h \in S_4 \times [-0.5, 0.5)$ $(j = 1, ..., Card(D^h))$.
Level 7: *Information sources*, consisting of all data sources within the Internet, such as databases and information repositories.

The activity of this Web multi-agent model is composed of two phases, retrieval and feedback.

3.1 Retrieval Phase

This first phase coincides with the information gathering process developed by the multi-agent model itself, i.e., this phase begins when a user specifies his/her query and finishes when he/she chooses his/her desired documents among the relevant documents retrieved and provided by the system. It is developed in the following steps:

Step 1: An *Internet user* expresses his/her information needs by means of a linguistic multi-weighted query. The 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 threshold $\{p_1^1, p_2^1, ..., p_m^1\}$ with $p_i^1 \in S_1$, and by a linguistic degree of relative importance $\{p_1^2, p_2^2, ..., p_m^2\}$ with $p_i^2 \in S_2$. Furthermore, in the first user-system interaction, user should define his/her profile $(\mathcal{P}_i)$ identifying their interests in each topic ranging from values of S_4. The user also expresses his/her identity $\mathcal{ID}$. All this information is given by the user to the *interface agent*.
Step 2: The *interface agent* gives the terms and their importance weights together with the user profile (in the first time) to the *collaborative filtering agent*.
Step 3: The *collaborative filtering agent* gives the terms and their importance weights to the *task agent*.
Step 4: The *task agent* communicates the terms of the query and their importance weights to all the *content-based filtering agents* to which it is connected.
Step 5: Each *content-based filtering agent h* makes the query to its respective *information agent h* and gives it the terms of the query $\{t_1, t_2, ..., t_m\}$.
Step 6: All the *information agents* that have received the query, look for the documents that better satisfies it in the *information sources*. Documents are represented in the *information sources* using an index term based representation as in Information Retrieval [1, 13, 14]. Then, there exists a finite set of index terms $T = \{t_1, ..., t_l\}$ used to represent the documents and each document d_j is represented as a fuzzy subset $d_j = \{(t_1, F(d_j, t_1)), ..., (t_l, F(d_j, t_l))\}, F(d_j, t_i) \in [0, 1]$, where F is any numerical indexing function that weights index terms according to their significance in describing the content of a document. $F(d_j, t_i) = 0$ implies that the document d_j is not at all about the concept(s) represented by index term t_i and $F(d_j, t_i) = 1$ implies that the document d_j is perfectly represented by the concept(s) indicated by t_i.

Step 7: Each *content-based filtering agent h* receives from its respective *information agent h* a set of documents and their relevances (D^h, R^h) ordered decreasingly by relevance. Every document d_j^h has an associated linguistic degree of relevance $r_j^h \in S_4 \times [-0.5, 0.5)$ which is calculated as

$$r_j^h = \overline{x}^e[\Delta(g \cdot F(d_j^h, t_1)), \dots, \Delta(g \cdot F(d_j^h, t_m))] = \Delta(g \cdot \sum_{i=1}^{m} \frac{1}{m} F(d_j^h, t_i)),$$

being $g+1$ the cardinality of S_4. Each *content-based filtering agent h* filters documents received from its respective *information agent h* by recalculating their relevance by means of a linguistic matching function $e_h : (S_4 \times [-0.5, 0.5)) \times S_1 \rightarrow S_4 \times [-0.5, 0.5)$, which is defined to model the semantics of threshold weights associated with the query terms. This linguistic matching function requires a previous transformation of threshold weights expressed in labels of S_1 that must be transformed in labels of S_4, to make uniform the multi-granular linguistic information, we chose the linguistic term set used to express the relevance degrees. We use the transformation function viewed in Definition 6, $(TF_{t'}^{t})$, to transform the linguistic labels in level S_1 (t) to labels in level S_4 (t'), and then we obtain new linguistic threshold weights $\{p_1^{1'}, p_2^{1'}, ..., p_m^{1'}\}$, $p_i^{1'} \in S_4$ for the terms $\{t_1, t_2, ..., t_m\}$. Then, each *content-based filtering agent h* calculates a new set of relevance degrees $RN^h = \{rn_j^h, j = 1, ..., card(D^h)\}$ characterizing the documents D^h, which is obtained as

$$rn_j^h = \overline{x}^e[e_h(\Delta(g \cdot F(d_j^h, t_1)), p_1^{1'}), ..., e_h(\Delta(g \cdot F(d_j^h, t_m)), p_m^{1'})] =$$

$$\Delta(\sum_{i=1}^{m} \frac{1}{m} \Delta^{-1}(e_h(\Delta(g \cdot F(d_j^h, t_i)), p_i^{1'}))).$$

Step 8: The *task agent* receives from every *content-based filtering agent* a set of documents and their new relevance (D^h, RN^h). It also receives a set of linguistic degrees of satisfaction $C^h = \{c_1^h, c_2^h, ..., c_m^h\}$, $c_i^h \in S_3 \times [-0.5, 0.5)$ of D^h with regard to every term of the query as

$$c_i^h = \overline{x}^e[e_h(\Delta(g \cdot F(d_1^h, t_i)), p_i^{1'}), ..., e_h(\Delta(g \cdot F(d_{card(D^h)}^h, t_i)), p_i^{1'})] =$$

$$\Delta(\sum_{j=1}^{card(D^h)} \frac{1}{card(D^h)} \Delta^{-1}(e_h(\Delta(g \cdot F(d_j^h, t_i)), p_i^{1'}))).$$

Then, the *task agent* selects the number of documents to be retrieved from each *content-based filtering agent h*. So, it applies the following three steps:
Step 8.1: The *task agent* orders D^h with respect to the new relevance RN.
Step 8.2: The *task agent* aggregates both linguistic information weights, the satisfactions of the terms of the query from every *information agent*, (c_i^h, α_i), $c_i^h \in S_3$, and the importance weights that the user assigned to these terms, (p_i^2, α_i), $p_i^2 \in S_2$, using the aggregation process for fuzzy multi-granular linguistic information presented in [12], which is composed of two phases:

1. *Normalization Phase*: The linguistic term set used to express the relevance 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 $\{[(p_1^2, \alpha_1), (c_1^h, \alpha_1^w)], ..., [(p_m^2, \alpha_m), (c_m^h, \alpha_m^w)]\}$, $p_i^2 \in S_2$ *and* $c_i^h \in S_3$ be the set of pairs of importance and satisfaction to be aggregated by the task agent for every information agent h. Then, for combining them first the linguistic 2-tuples values $(p_i^2, \alpha_i), p_i^2 \in S_2$ and $(c_i^h, \alpha_i^w), c_i^h \in S_3$ are transformed in the linguistic term set used to express the relevance degrees, in this case S_4, obtaining their corresponding values $(p_i^{2'}, \alpha_i')$, $p_i^{2'} \in S_4$ and $(c_i^{h'}, \alpha_i^{w'})$, $c_i^{h'} \in S_4$. Once the fuzzy 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 $\lambda^h = \overline{x}_l^w([(p_1^{2'}, \alpha_1'), (c_1^{h'}, \alpha_1^{w'})], ..., [(p_m^{2'}, \alpha_m'), (c_m^{h'}, \alpha_m^{w'})])$.

Step 8.3: To gather the best documents from *content-based filtering agents*, the *task agent* selects a number of documents $k(D^h)$ from every *content-based filtering agent h* being proportional to its respective degree of satisfaction λ^h, $k(D^h) = round(\frac{\sum_{i=1}^{n} card(D^i)}{n} \cdot P_s^h)$, where $P_s^h = \frac{\Delta^{-1}(\lambda^h)}{\sum_{i=1}^{n} \Delta^{-1}(\lambda^h)}$ is the probability of selection of the documents from *content-based filtering agent h.*

Step 9: The *collaborative filtering agent* receives from the *task agent* a list of documents $DV = \{d_1^V, ..., d_v^V\}$ ordered with respect to their relevance RV, such that, i) $r_j^V \geq r_{j+1}^V$, ii) for a given document $d_j^V \in DV$ there exists a h such that $d_j^V \in D^h$ and $r_j^V \in RN^h$, and iii) $card(DV) = v \leq \sum_{i=1}^{n} k(D^i)$.

Then, *collaborative filtering agent* filters the documents provided by the *task agent* using the recommendations on such documents provided by other users with similar preferences (checking their profile) in previous searches. These recommendations are stored together with user profiles in a *collaborative recommender system.* This is done in the following steps:

Step 9.1: The *collaborative filtering agent* asks *collaborative recommender system* the recommendations existing on DV of that users with a similar profile to the active user $(\mathcal{P}_i)$ and retrieves them, $RC^{\mathcal{P}_i} = \{RC_1^{\mathcal{P}_i}, ..., RC_v^{\mathcal{P}_i}\}$, $RC_j^{\mathcal{P}_i} \in S_5 \times [-0.5, 0.5)$.

Step 9.2: The *collaborative filtering agent* filters the documents by recalculating their relevance using these recommendations $RC^{\mathcal{P}_i}$. Then, for each document $d_j^V \in DV$ a new linguistic relevance degree r_j^{NV} is recalculated from r_j^V and $RC_j^{\mathcal{P}_i}$ by means of the 2-tuple weighted operator $\overline{x}^w$ given in Definition 4: $r_j^{NV} = \overline{x}^w(r_j^V, RC_j^{\mathcal{P}_i})$, using, for example, the weighting vector $W = [0.6, 0.4]$.

Step 10: The *interface agent* receives from the *collaborative filtering agent* a list of documents $DW = \{d_1^W, ..., d_w^W\}$ ordered with respect to their relevance RW, such that, i) $r_j^W \geq r_{j+1}^W$, ii) for a given document $d_j^W \in DW$ there exists a i such that $d_j^W = d_i^V$ and $r_j^W = r_i^{NV}$, and iii) $card(DW) = w \leq v = card(DV)$.

Then, the *interface agent* filters these documents in order to give to the user only those documents that fulfill better his/her needs, which we call D_f. For example, it can select a fixed number of documents K and to show the K best documents.

3.2 Feedback Phase

This second phase coincides with the updating process of collaborative recommendations on desired documents existing in the collaborative recommender system, i.e., this phase begins when the *interface agent* informs the documents chosen by the user to the *collaborative filtering agent* and finishes when the recommender system recalculates and updates the recommendations of the desired documents. In collaborative recommender systems the people collaborate to help one another to perform filtering by recording their reactions to documents they read [19, 27]. This feedback activity is developed in the following steps:

Step 1: The *interface agent* gives the user's identity $\mathcal{ID}$ (usually his/her e-mail) together with the set of documents $DU = \{d_1^U, ..., d_u^U\},\ u \leq card(D_f)$ used by the user to the *collaborative filtering agent*.
Step 2: The *collaborative filtering agent* asks user his/her opinion or evaluation judgements about DU, for example by means of an e-mail.
Step 3: The *Internet user* communicates linguistic evaluation judgements to the *collaborative recommender system*, rc_y, $y = 1, ..., card(DU),\ rc_y \in S_5$.
Step 4: The *collaborative recommender system* recalculates the linguistic recommendations of set of documents DU by aggregating again the opinions provided by other users together with those provided by the Internet user. This can be done using the 2-tuple aggregation operator $\overline{x}^e$ given in Definition 3. Then, given a chosen document $d_y^U \in DU$ that receives a recommendation or evaluation judgement rc_y from the Internet user, and supposing that in the collaborative recommender system there exists a set of stored linguistic recommendations $\{rc_1, ..., rc_M\},\ rc_i \in S_5$ associated with d_y^U for the user profile $\mathcal{P}_i$, which were provided by M different users in previous searches, then a new value of recommendation of d_y^U is obtained as $RC_y^{\mathcal{P}_i} = \overline{x}^e[(rc_1, 0), ...(rc_M, 0), (rc_y, 0)]$.

4 Concluding Remarks

We have presented a new fuzzy linguistic Web multi-agent model where the communication processes carried out in the information gathering are modeled by means of the fuzzy multi-granular linguistic information. To do so, we have used the hierarchical linguistic contexts and the 2-tuple linguistic computational model. The use of the fuzzy multi-granular linguistic information allows a higher flexibility and expressiveness in the communication among the agents and between users and agents in the information gathering process and it does not decrease the precision of system in its results and the complexity of the processes is not increased.

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