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St-Jacques, C., and Paquin, L.-C.
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Dynamic Visualization of Information: From Database to Dataspace

Claude St-Jacques*, **and Louis-Claude Paquin****

*University of Ottawa
Ottawa, ON, KIN 6N5, Canada
E-mail: stjacque@site.uottawa.ca
**Université du Québec à Montréal
Montréal, QC, H3C 3P8, Canada
E-mail: paquin.louis-claude@uqam.ca

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This paper explores a generalization of the Teleweb project [1] through an XML protocol. The research aims to provide friendly online access to large multimedia databases where the "content or topic" of the media units of texts, sounds or video, is indexed with an arbitrary set of descriptors. Among others, the deliverables of Teleweb consist of a mapping algorithm for a dynamic broadcast and a visualization interface. To go beyond the cognitive limitations of listings as results of database requests, we design an original solution: a topological representation into a 3D image of the relationship among the respective units. Instead of browsing through lists of thousands of units, ten at a time, the user is engaged in a dynamically created immersive environment, where he can control his own navigation over the information. To model the relationship of proximity between units, we use the soft computing capability of the fuzzy logic. Converted into topological data, the degree of the relationship of one unit with another is used to generate a space by soliciting the user's cognitive skills of visual perception instead of by memorization. The database then becomes a data-space.

Keywords: multimedia database, topological representation, visualization, cognitive ergonomics, fuzzy logic

1. Problem of Listings

We are currently generalizing the algorithms and the interface produced in a media art context to the field of Information Sciences. Our research, undertaken three years ago, is oriented towards the augmentation of human intellectual skills to deal with large sets of information pieces (between 200 and 2000) in one stance. Instead of the usual browsing through listings, cut into screens of tenths of information pieces, we are combining an ecological approach of cognitive science with the soft computing of fuzzy logic to put forward a significant representation of the whole information about units on one and only one screen. To us, this seems more suitable for human beings, as they have very small short-term memories but highly effective spatial perceptual skills.

Listings are in file format with a tabular structure, i.e., one line for each record. They are also in linear sets of items. To access one item, the user has to browse through the sequence, depending on the ordering of the units. Arbitrary sorting, such as alphabetical, temporal or thematic, is the only means of optimization. In fact, listings are a purely machinist means of communicating the information throughout computer processes, but not for human beings. Listings linearity prevents the user from constructing a representation of the distribution of the listed units and their relationships. Such cognitive operations enable the formation and the closure of a semantic domain.

Two approaches are then possible: the replacement of the human reasoning with the expert systems of the Artificial Intelligence project or the augmentation of the human intelligence with the proper algorithms and ergonomic interfaces. The former solution consists of a dynamic sorting process that presents only the ten best candidates in the list ordered by relative relevancy in regards to criteria, such as the frequency of searched terms, their position in the document, etc. The latter solution, discussed in this paper, is visualization.

2. Problem of Indexation

In the Teleweb project, the media files from a database were indexed by their author who was using a set of descriptors ranging from general to specific. Those descriptors are both thematic and semantic markers of the media file content, that is to say of what is represented. We plan to extend the application of our approach to the more general context of the information systems of a library or a documentation center. These systems rely on a database that references documents based on usual properties, such as the title, the author's name, and the publishing information. However, the descriptors aim to solve the silence and the problematic noise, except that they are simultaneously multiplying the access to the documents by their key conceptual uses and restraining all other conceptual accesses to those that are strongly thematized. Therefore, the silence becomes the rate for relevant documents not returned by a query concerning a specific topic and the noise is all the irrelevant documents returned by the same request.

Adding descriptors, usually taken from a thesaurus, is a highly specialized task for someone being able to recognize and extract the thematized concept of a document. This task relies on individuals to have their own background knowledge, their own expertise acquired by their past practices, and by their own inclinations and saliencies according to their personality traits. Because of all of that, each person has her own particular way of indexing and there is no guaranty that the same document will get the same descriptors from different people. Even if the descriptors are rigorously classified into a thesaurus, the resulting indexation is under-determined or otherwise chaotic. Nevertheless, we aim to construct the spatial representation of documents by using some semantic dimensions pertaining to the descriptors, not only because the user might find them relevant to the documents, but also because he can perform a "knowledge discovery" [2] following their distribution in a space.

3. Visualization

Visualization aiming to facilitate and enrich the human action and his experience of information optimization of the apprehension and comprehension, coming from cognitive skills related to the spatial perception through a visual computation, has both fantasmatic[1] and scientific origins [4]. The object constancy eliminates the need for their re-assimilation into a listing. The following is a brief survey of the theorization and the realization of this process.

Like in the Cartesian plan, the space could be treated as if it might possess a metrical structure. The visualization is a process used to graphically encode and display the object's relationships, such that their similarities and differences with regards to their positions and several retinal variables: color, size, grain, form, orientation according to an arbitrary semiotic. Data can be projected or mapped onto topological spaces with 2 or 3 orthogonal axis. Mackinlay [5] defined the criteria of expressivity and efficiency extended to the interactivity by Beshers and Feiner [6]; visualization is expressive, if and only if, the whole units of relevant information are present; visualization is efficient if these conditions are clearly presented.

The spatial repartition of the visual structures or clusters is determined in accordance with a linear or radial axis [7]: 1) unstructured: no axis; 2) nominal axis: area /sub-area; 3) ordinal axis: ordered sub-area; and 4) quantitative axis: the area has a metric unit. Among those that use 2 orthogonal axes, there is hyperbolic tree [8]: clicking a node on the map changes the focus, and all the others are reordered in front of this item. Some use 2 axes for linear structures to simulate the third one as a perspective wall [9] suited for the linearly structured information. A perspective view overcomes the limitation of the screen and gives an idea of the totality of the information. Some others use the 3 axes to create data spaces, like hills and valleys, where the relationship between the information units is mapped as a hill for strongly related items and as a valley when their relationship is shared.

We choose hills and valleys as representations because the possible interactions, such as to fly over, to dive in and to take off, go beyond the selection of relevant units and enable the user to produce his own ThemeScape by exploring the data-space. The user interacts with a data-space by means of visual transformation [10], since he can fluently change his point of view of the visual structures by using the mouse. Consequently, he explores the data-space by controlling the camera movement in relation to the rendering.

The regularity that we are looking for, with such ergonomics, is one of a virtual world that adapts itself to the need of a user and which cognitively engages him. As the starting point of our design, we take the recent work in neurophysiology and neuropsychology, showing that the crystalline organization of the primary visual cortex of mammal brains enables information solving, that is conceivable by modeling it with Gabor wavelet theory [11]. Researchers in cognitive science [12, 13] consider that model as ideal as that of a human face for image recognition. Since information resolution by a visual cortex can be modulated by Gabor's function and a Gaussian curve [12], this modeling is appropriate in extenso for our 3D representation of hilly ground.

Furthermore, Bierderman's theory [14] of geons (geometrical ions) shows that human beings spontaneously perceive simple visual perspectives like the bottom or the top of an object as well as its width and length. In that case, we can transpose these invariants into a perspective that spontaneously highlights the magnitude of the semantic relations involved between the objects into such a virtual data-space. That is to say, the position of an object on the side of a mountain can directly give its amplitude of similarity in comparison to the other ones in the group, exactly as a sensitive representation as our visual abilities express it: higher near the top and lower as it approaches the bottom. In the same way, the amplitude of the difference into a data-space is immediately perceivable by the extent of each mountain: what belongs distinctively to the extent in the width of a mountain belongs in the same manner to a group of objects, and where the limits between two mountains are indistinct or overlap, it is the same for the groups.

Such a topological mapping in a three dimensional space seems very attractive to us, because the query of a user launches the cybernetics of semantics, which cognitively engages this one by spontaneously requesting its visual perception to determine the amplitude of these relations transposed in a sensitive representation. By means

1. "A graphical representation of data abstracted from the banks of every computer in the human system. Unthinkable complexity. Lines of light ranged in the non-space of the mind, clusters and constellations of data. Like city lights, receding. . .." See [3] p. 51.

Table 1. A record in a database.

—53—
Title:
Computational explorations in cognitive neuroscience: understanding the mind by simulating the brain
Subject:
Cognitive neuroscience; Computer simulation; Cognitive process; Computational neuroscience; Brain; Neural net (biological);

Table 2. Matrix of weighted terms.

Document #	**Terms**
...	...
53	computational (3), cognitive (4), neuroscience (4), ...
54	process (3), cognitive (4), modeling (3), ...
...	...

of a cybernetic loop, we involve the user in an immersive environment in such a way that sometimes he takes the control, at first for the semantics parameters of the adaptability, then the machines controls the principles of regularity, then the user takes control again by navigating, and finally the machine controls the whole sensorial apparatus of the human by his immersion in a virtual reality.

4. Computational Framework

The design of our navigation tool is based on a model of cognitive ergonomics since the tool acts as a source of augmented intelligence on the user by means of man-machine interactions. We set up our strategy of intelligent informatics on the use of three regulating principles naturally emerging from the objects into media spaces. The resemblance, the difference, and the data-space of each object are the three perceptual invariants used to design a significant visualization of multimedia databases for the users.

Starting from the fact that the information about the documents in multimedia databases is given in the standard mode of informatics (see **Table 1**), i.e., by title, subjects and keywords, a user must be able to cut out a query with few words from the relevant units for his search. According to Miyamoto [15], we attempt to retrieve resembling documents into a database through their fuzzy associations.

Consider that two sets T and P are given by a multimedia database: $T = \{t_1, t_2, \ldots, t_n\}$ being the set of index terms used to describe the documents and $P = \{p_1, p_2, \ldots, p_m\}$ being the set of pictures coming from each unit. A picture[2] is an abstract entity when it serves to express a state of affairs produced by the description of a document in a natural language. Since the picture P of a data-space cannot be found directly in the world, we can represent it by a fuzzy set $f : T \to [0,1]$. That is to say, a relation R of a fuzzy association between $\langle t_i, p_j\rangle$ can be expressed by a function f being one of the abstract descriptions of p_j characterized by $\mu_f(t_i)$ the grade of membership of term t_i to it, in such a way that

$$f(t_i) = \{t_i | \langle t_i, p_j\rangle \in R\}. \qquad (1)$$

According to [15], we can substitute the set $\Delta = \{\delta_1, \delta_2, \ldots, \delta_m\}$ of documents to the abstract set of picture P and use the frequencies of occurrence of terms t_i in the description of δ_j to grade this function. In our first experiment, we choose to account for the double occurrence of a term in the title by making the hypothesis that words are more significant to that place. As we show in **Table 2**, we can build a matrix from the vectors of weighted terms representing each document.

Because this method of weighing the terms in a document δ_j is one amongst many others, we denote this substitution by the function f^*:

$$f^*(t_i) = \{t_i | \langle t_i, \delta_j\rangle \in R\} \qquad (2)$$

Thus, for each term in a document, the term's membership degree is given by:

$$f_j^*(t_i) = \left(\mu_{f_1^*}(t_1)\right)/\delta_1 + \left(\mu_{f_2^*}(t_2)\right)/\delta_2 + \ldots + \left(\mu_{f_m^*}(t_n)\right)/\delta_m. \qquad (3)$$

Despite the under-determined structure of the vocabulary into multimedia databases, built under a collaborative but non-normalised mode, a human being has the innate ability to cognitively identify in his mind the resembling objects in that space. But a human is unable to do it in one stance when objects are in a huge database. If we simulate this cognitive ability to seize all of the similarities between objects in one synthetic glance by using an artefact, such as a tool, it becomes an extension of human intelligence. As Ref.[15] suggested with its intelligent informatics method, the result of a search can be improved by expanding the query of a user; whereas, the specific terms that he used could be inadequate.

Along with that theory [15], we can automatically build

2. Parallels can be made here between our use of picture and how [15] uses a concept to describe the mental state produced by the understanding of the description of a document. We borrow from Wittgenstein [16] the idea that a state of affairs from the real world generates a picture in our mind.

a pseudo-thesaurus of related terms from our matrix of documents by computing their fuzzy similarities with the formula:

$$Sim(t_h, t_i) = \frac{\sum_j \min\left(\mu_{f_j^*}(t_{hj}), \mu_{f_j^*}(t_{ij})\right)}{\sum_j \max\left(\mu_{f_j^*}(t_{hj}), \mu_{f_j^*}(t_{ij})\right)}. \quad . \quad (4)$$

The fuzzy similarity connecting terms t_h and t_i, of which the membership degree to a document δ_j is given by eq.(3), is computed by the *min* value between their weights and amongst all of their co-occurrences into the j documents, divided by the *max* value of the same kind of co-occurrences across the j documents.

Hence, if a user gives the weight of term t_g used, then the following fuzzy set can represent his query:

$$Q = \left(\mu_Q(t_g)\right)/t_1 + \left(\mu_Q(t_g)\right)/t_2 + \ldots + \left(\mu_Q(t_g)\right)/t_n. \quad (5)$$

After that, the terms chosen by the user can be automatically projected onto the set of related terms in the pseudo-thesaurus and produce the following fuzzy set B of associated terms:

$$B = \left(\mu_B(t_{gi})\right)/t_1 + \left(\mu_B(t_{gi})\right)/t_2 + \ldots + \left(\mu_B(t_{gi})\right)/t_m. \quad (6)$$

Therefore, the weight of an expanded query depends on both fuzzy sets Q and B. Let us call E the fuzzy set resulting from that expansion and express what is expected as $E = \bigcup_{t_i \in T} \left(\mu_Q(t_g)\right) \cap \left(\mu_B(t_{gi})\right)$. The evaluation of that compositional relation can be done by using the logical operators *max min*: $E = \max_{t_i}[\min\left(\mu_Q(t_g), \mu_P(t_{gi})\right)]$. Then the expanded query is

$$E = (\mu_E(t_i))/t_1 + (\mu_E(t_i))/t_2 + \ldots + (\mu_E(t_i))/t_n. \quad (7)$$

Now we are ready to implement our first regulating principle, i.e., in one glance to seize the resemblance between the objects of the data-space. As before, the relation of the *max-min* composition can be used to compute the similarity between pictures by comparing the weights of each unit, given by the function of substitution (3), with the expanded query (7). If we call f^{**} the fuzzy set obtained from $f^{**} = \max_{d_j \in D}\left[\min\left(\mu_E(t_i), \mu_{f^*}(t_i)\right)\right]$ composition, the result is given by

$$\begin{aligned} f_j^{**}(t_i) &= \left(\mu_{f_1^{**}}(t_1)\right)/\delta_1 + \left(\mu_{f_2^{**}}(t_2)\right)/\delta_2 + \ldots \\ &\quad + \left(\mu_{f_m^{**}}(t_n)\right)/\delta_m. \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (8) \end{aligned}$$

By debating the question of the visualization of a database one step further, we state that no data-space is reserved for objects when they are presented in a list like (8) and eventually sorted out by grade. It is where the computation on databases generally stops without any global perspective of the objects. However, it could be possible for a user to appreciate the granularity that distinguishes the documents if each object had its own data-space. The nature of this characteristic immediately emerges from a group of objects having a minimum amount of resemblance[3] when we consider their differences in a data-space.

As we said before, $P = \{p_1, p_2, \ldots, p_m\}$ is the set of pictures coming from each unit in a data-space and we can enhance that $P \neq \emptyset$ for any database having at least one element. So, one p cannot exist alone without the differences which its nature gives to it in comparison to another. Let G be the set of aggregates formed by the granularity of the documents in a data-space when we compare the difference between the resemblances of their descriptions made in natural language. According to Höppner et al.'s [17] analysis of space theory and eq.(1), we can say:

$$A(P, G) = \{f \mid f: T \to C, T \subseteq P, T \neq \emptyset, C \in G\}. \quad (9)$$

We should read that the analysis A of granularity G of the picture P of a database is given by the function f, in such a way that the fuzzy sets T of index terms describing a unit entail the partition of the data-space in a set of clusters C. Since we can say from (1) and (2) that $T \subseteq P$ and from $P \neq \emptyset$ that $T \neq \emptyset$, then the set of clusters C is a mapping of the granularity G.

In spite of the under-determined or chaotic nature of a data-space, what produces the regrouping of documents is the common features that they partake in with others. The fuzzy cluster analysis [17, 18] put forward a flexible method to make an objective partition of a data-space. That strategy comes from the following basic function:

$$J(f) = \sum_{p_j \in P} \sum_{c \in C} f^m(p)(c) \cdot d^2(p, c). \quad . \quad . \quad . \quad (10)$$

This formula is called an objective function [18] $J(f)$ because it makes the computation of the arbitrary function $J : A(P, G)$ in our application, in which one tries to minimize the distance between a picture p and a cluster c and the membership[4] of a picture p to a cluster c in regards to the function f. As we said before, for the picture P of a data-space, we cannot directly find the distance $d^2(p, c)$ in the world, nor can we find the membership $f^m(p)(c)$ of a picture to a cluster, because they are abstract entities.

Nevertheless, as an objective function, we can use the computation of the square distance error $(d_{ik})^2$ between the vectors of terms t_i representing a unit δ_j in the data-space and the prototypal vector v_k of a cluster c. Such a Euclidean distance can be iteratively computed by the formula:

$$\begin{aligned} d_{ik} &= d(t_{ij}, v_{kc}) = \left\|t_{ij} - v_{kc}\right\| \\ &= \left[\sum_{c \in C} \left(t_{ij} - v_{kc}\right)^2\right]^{1/2}. \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (11) \end{aligned}$$

The distance function now being a real value in a Euclidean space, we can next calculate the membership degree of a unit δ_j to a cluster c at each iteration by using the following formula:

$$\mu_c(t_{ij}) = 1 \Big/ \sum_{c \in C} \left(d_{ik}^2 / d_{jc}^2\right)^{\frac{1}{m-1}} \quad . \quad . \quad . \quad . \quad . \quad . \quad (12)$$

where $d_{jc} = \sum_c d_{ik}^2$.

By denoting the fuzzy set generated by (12) f^χ,

3. Remember that we already made sure to have resembling objects by doing a query based on the fuzzy similarities.

4. See [17] p. 22 for the explanation of how to choose the memberships $f(p)(c)$, $p \in P$, $c \in C$ in order to minimize the objective function.

Table 3. Sample of the cluster analysis.

Document (#)	Cluster (#)	$\mu_c^m(t_{ij})$	d_{ik}^2
157	**1**	**0.946684**	**0.00215533**
	2	0.0121608	0.167787
	3	0.00758878	0.268874
	4	0.0164925	0.123718
	5	0.0114789	0.177754
	6	0.00559484	0.364697
218	1	0.0639967	0.146014
	2	**0.704455**	**0.0132648**
	3	0.0723267	0.129198
	4	0.0644457	0.144997
	5	0.0662716	0.141002
	6	0.0285043	0.327826
71	1	0.038741	0.253508
	2	0.0801183	0.122583
	3	**0.780623**	**0.0125812**
	4	0.0378632	0.259385
	5	0.0405594	0.242143
	6	0.0220946	0.444504

the normalized values of the membership to a cluster $(\mu_c(t_{ij})/\sum_c \mu(t_{jc}))$ by F and the set of prototypes of a data-space V, we can rewrite (10) as follows:

$$J(T, f^\chi, F, V) = \sum_{\delta_j \in \Delta} \sum_{c \in C} \mu_c^m(t_{ij}) \cdot d^2(t_{ij}, v_{kc}). \quad (13)$$

The optimization of (13) can be computed iteratively with the eqs.(11) and (12) until a threshold value of a change in the membership degrees to the clusters is attained, i.e., $\left\|F^{n-1} - F^n\right\| \leq \varepsilon$, or a maximum number of iterations has been executed. We refer to the work of [17, 18] for the details concerning the calculation of the objective function. Nevertheless, we must stress that the position of the prototypes should be recomputed at each cycle, since J is dependent on the Euclidean distance (11) between the data vector and the prototype. So, the update of each vector prototype is obtained by computing the mean of the membership degrees of data vectors to a cluster as follows:

$$v_{kc} = \sum_c \mu_c^m(t_{ij}) \Big/ \sum_c \mu^m(t_{jc}). \quad \dots\dots \quad (14)$$

As noticed in [1], we use the free software [19] under Linux to create a regrouping of documents following the granularity found by these “fuzzy clustering algorithms”. This program makes it possible to automatically determine the optimal number of clusters by using a vote of three validity measures: the partition and entropy coefficients, and a measure of compaction and separation between the clusters. In **Table 3** we show a sample of the cluster analysis obtained from the database extraction made with the query “autism”.[5]

As we can see in **Table 3**, the program of fuzzy clustering analysis regroups the similar documents into 6 clusters following the granularity discovered by design. This means that documents 157, 218 and 71 belong respectively more to the clusters 1, 2 and 3. Hence, we take notes that the differences among the resembling documents emerge naturally from the objects when we use a clustering analysis for the detection of the granularity connecting them.

Let us examine now how we can make use of the results obtained from the modeling of the first two perceptual invariants, i.e., the resemblance and the difference, to give form to our third one: a visual representation sensitive to the data-space. We should stress beforehand, that we are talking about data-space as a position of data taken dynamically in the space according to the perspective taken at first by a user with his query. A little variation in the choice of the keywords used for a search in a database must proportionally affect the position of a data in the space. So, a sensitive representation to cognitive ergonomics should reflect this change in the mind of a user.

In order to produce such a topological mapping sensitive to the selected perceptual invariants, we should look at some difficulties that confront us when we accept the objects in the database in their own nature. The vectors of terms describing the documents are multidimensional, whereas our topological representation must be in 3D. One solution has been proposed by [17] who explored the idea of representing clusters by a 3D visualization. They borrowed a strategy for the reduction of the vectors' sizes from multidimensional to tri-dimensional from the fuzzy controller's theory. This idea is based on a fuzzy function approximation derived from fuzzy inference rules.

Let us first say that the function we are trying to approximate is the Gaussian curve for the modeling of the hilly ground. According to [17], the coordinates of each object onto a mountain can be computed by using the following bell-shaped function:

$$\mu_c(t_{ij}) = e^{-\left(\|t_{ij} - v_{kc}\|/\sigma_c\right)^\alpha}. \quad \dots\dots\dots\dots \quad (15)$$

Note that σ and α are parameters respectively for the standard deviation and the mean of the curve. In **Table 3** we can see that the value of $\mu_c(t_{ij})$ is already known from eq.(12) when the objective function (13) gives an optimal partition of the data-space. As we said before, these values would express the degree of similarity between objects into the same cluster following their elevation on the side of a mountain. So, the membership degree to a cluster will be the z coordinate into the data-space. After that, there is an easy way to locate the position of a unit t_{ij} on a mountain if we are able to determine the x and y coordinates of a prototype v_{ck}: by computing the distance $\left\|t_{ij} - v_{ck}\right\|$ between the unit and the prototype. That is to say, we can derive this value from eq.(14) as follows:

$$\left\|t_{ij} - v_{ck}\right\| = -\sigma_c \left(\ln \mu_c(t_{ij})\right)^{1/\alpha}. \quad \dots\dots\dots \quad (16)$$

To be exact, the position of the prototype must be exactly where a vertical line passes through the center of the top of a mountain in the data-space, and that distance could be anywhere on the circle around that central pole. Since eq.(16) serves only as a template for our visualiza-

5. We use the same query as in [1], except that we apply a lower alpha-cut on the results and this is the reason why we obtain one more cluster.

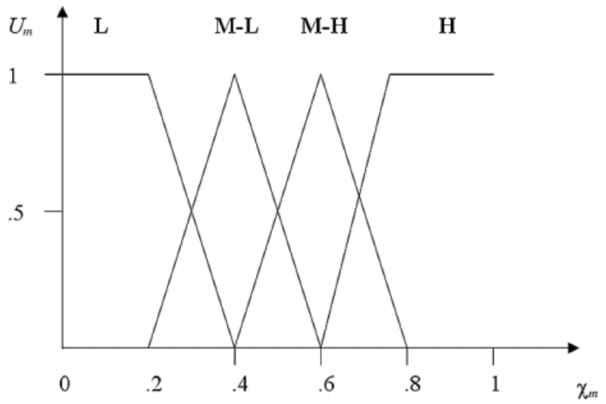

Fig. 1. Fuzzy sets of the "if" part for the rules.

tion interface and the z coordinate being given, the position of a unit t_{ij} on that circle around this central pole can be settled randomly.

However, (16) cannot be evaluated before the reduction of the vectors' sizes of the prototypes v_{ck} from multidimensional to bi-dimensional x and y coordinates. This is where we would use the fuzzy controller's theory to approximate that function. Remember that fuzzy controllers consist of a fuzzy rule base that represents an imprecise linguistic description of the manner of control states being explicitly uttered by human operators in regards to control a system [20]. The rule base could be expressed by n fuzzy inferences having the following schema:

If χ_1 is U_1 and χ_2 is U_2 ... and χ_m is U_m
then Y_1 is W_1. . . . . (17)

In an experiment, like the one shown in **Table 3**, we extracted some documents δ_j (or vectors of terms t_{ij}) with eq.(8) and that gave us the final values of (14) the prototypes v_{kc} at the end of the optimisation of eq.(13). In that example, we obtained 6 prototypal vectors, each one being associated to a cluster center by which the aggregated units are best represented. After the optimisation of eq.(13), the vectors of terms have the form $f(\chi_1, \chi_2, \cdots, \chi_m) = y$ in accordance with the function f^{χ}, i.e., they are entailing the typicality of only one conclusion y more specifically than the others. So, our strategy is to approximate that function and then reduce it to $f(\chi) = y$.

Considering that neural networks are good approximators of functions in the fuzzy controller applications, we use the free software NEFCLASS-J [21] to find the rules governing the emergence of the class of objects without human intervention. Therefore, we can give as input to this fuzzy classifier the same vectors of terms t_{ij} (extracted with (8)) and then the ones utilized in the fuzzy clustering analysis by specifying to which cluster each one pertains.

As a result, a rule like (17) is automatically generated for each cluster of vectors by the NEFCLASS supervised learning algorithm, and fuzzy sets are iteratively adapted to each premise (χ_m) of a rule. For instance,

Table 4. Coordinates of the center pole of the mountains.

Cluster (#)	*x*	*y*
1	0.27	0.25
2	0.40	0.28
3	0.28	0.34
4	0.73	0.25
5	1	0.12
6	0.52	0.50

Fig.1 sketches the triangular-shaped fuzzy sets generated by NEFCLASS for every premise of the experiment partially shown in **Table 3**.

To arrive at the reduced function $f(\chi) = y$, we apply a kind of reasoning typical to the fuzzy controllers. Specifically, we proceed to find the height of association for each rule (17) through the m antecedents χ is U by using the fuzzy standard intersection. For example, the data of the first prototypal vectors of this trial are $\langle$0.001, 0.001, 0.026, 0.008, 0.254, 0.002, 0.001, 0.008, 0.133, 0.036$\rangle$. Then, NEFCLASS tells us which fuzzy set between Low (L), Medium-Low (M-L), Medium-High (M-H) and High (H) on **Fig.1** applies for each of these ten dimensions of the prototype corresponding to the rule discovered. These are respectively [L, L, L, L, M-L, L, L, L, L, L]. By relating these with the parameters of the prototypal vector given above, we obtain the fuzzy numbers denoting the antecedents on which we apply the standard intersection $f(\chi)= min$ [1, 1, 1, 1, 0.27, 1, 1, 1, 1, 1], i.e., $f(0.27) = y$. Since the fourth feature of that vector is the one giving the degree of consistency to the rule, we make the projection on that dimension and use the corresponding value in the prototype as the y coordinate. Thus, the x and y coordinates of the center pole of cluster 1 are (0.27, 0.25).

Concisely, as suggested by the method of the multidimensional reduction of [17], we can rely on the quantitative information obtained from the fuzzy c-mean [19] and the fuzzy classifier [21] computation to produce a sensitive representation of a data-space. Following that method, **Table 4** gives the x and y coordinates of the center pole of each cluster of the experiment related to **Table 3**.

As we explained before, we can subsequently compute the distance of a document to the coordinates of the center pole of the mountain to which it belongs in the data-space. In **Table 5**, the distance $\|t_{ij} - v_{ck}\|$ is given by eq.(16) when we use $\sigma = 1/8$ and $\alpha = 2$ as shaping parameters.

From the data of **Table 5**, we can now dynamically generate the picture P of the database of our experiment when a user searches for documents about "autism". Then, by using a bell-shaped function (14), we produce (see **Fig.2**) the data-space of each object which is proportional to the amplitude of their relations to the others when we look upon the resemblance and the difference among them. Therefore, a 3-D rendering of information from a database to a data-space makes it possible for a user to dynamically seize the semantics of the documents with one glance. For instance, the synthetic visualization of the data-space

Table 5. Elevation/Distance of each document into a cluster.

Document (#)	Cluster (#)	$\mu_c(t_{ij})$	$\|t_{ij} - v_{ck}\|$
157	1	0.95	0.03
243	1	0.65	0.08
270	1	0.45	0.11
194	1	0.31	0.14
218	2	0.70	0.07
81	2	0.55	0.10
60	2	0.39	0.12
18	2	0.24	0.15
71	3	0.78	0.06
65	3	0.66	0.08
236	3	0.54	0.10
287	3	0.26	0.14
58	4	0.95	0.03
21	4	0.50	0.10
222	4	0.39	0.12
40	4	0.24	0.15
9	5	0.89	0.04
174	5	0.68	0.08
10	5	0.51	0.10
94	5	0.24	0.15
19	6	0.97	0.02
73	6	0.74	0.07
63	6	0.45	0.11
11	6	0.18	0.16

shown in **Fig.2** enables the user to discover the typicality of each mountain: 1) Social aspect of cognition; 2) Institutional care for the cognitive disorders; 3) Cognitive disorder; 4) Children's knowledge and thinking; 5) Cognitive process of learning; 6) Children's mental process of thinking[6]. The navigation in this virtual world becomes a ludic activity since the human might interact perceptually in a man-machine dialogue producing an immersive visualization of what is a categorical perception of an understandable data-space.

5. Conclusion

Technically, the prototypal design of our navigator seems to produce what we want as an interactive visualization of information from a database to a data-space. We think that our attempt to accommodate the user with an under-determined database breaks the psychological barrier of its linear perception by founding a consistent 3D visualization onto three perceptual invariants: resemblance, difference and data-space. Remember that the invariance should be understood as a perceptual mechanism always present as a human cognitive process. In our innovative design, what is variable comes from the amplitude of the relations that human beings perceive in regards to the invariants when they visualize the picture of a database state of affairs.

In summary, we look at a database like Wittgenstein's picture theory of meaning [16], that is to say that a state of affairs is thinkable and we can picture it for ourselves. Therefore, our strategy to produce a relevant picture of a query is founded on the "Cybernetics of semantic"[7] whereas intelligent informatics serves to model the reality of that state of affairs in the database. By letting the human navigator build his own understanding of the data-space, our tool distinguishably turns out to be a source for augmented intelligence and a search becomes a game.

The relevance of the picture of a database state of affairs is the perspective that we should validate in our future work. After having achieved the module of visualization of our prototype, we plan to make trial of test among focus groups of users. Indeed, we wish to validate the cognitive assumptions of our design that certain perceptual invariants automatically stimulate the visual recognition of the pictorial information and thus work as predicted. Then, the next step will be to optimize our design to experiment with the navigation tool by applying it to a large database of information systems, like a library or a documentation center.

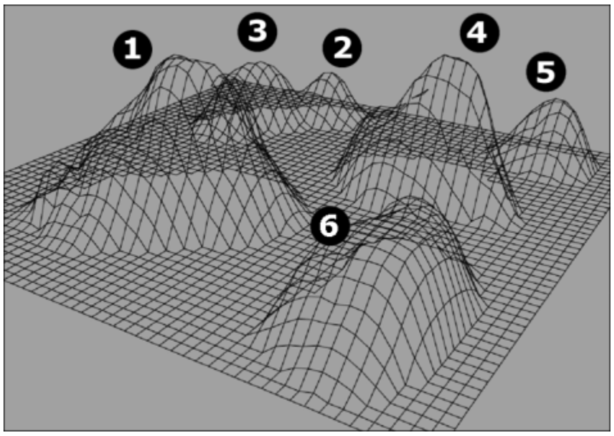

Fig. 2. Example of mountain rendering.

6. Notice that the themes of the groupings are the same ones as in [1] except for (2), which is a new group obtained by lowering the threshold of the alpha-cut in the present query with "autism". Because associated terms in an expanded query can be very large, we should determine the appropriate value for the threshold limiting the results to relevant documents. Moreover, it seems that lowering this threshold creates new groups that have less significance with the query. In the example here, the documents about the institutional care for the cognitive disorders refer to many more troubles than autism: senility, eating disorders, etc.

7. See [22] p. 94.

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Name:
Claude St-Jacques

Affiliation:
Part-Time Professor, Philosophy, University of Ottawa and Informatique, Université du Québec à Montréal; Visiting Worker, National Research Council Canada

Address:
Language Technologies Research Centre, 101, rue Saint-Jean-Bosco, pièce A-1330, Gatineau, Québec, K1A 0R6

Brief Biographical History:

2002-2003 Visiting Worker, Institut de Recherche en Informatique de Toulouse, France

2002-2004 Postdoctoral Fellow, School of Information Technology and Engineering, University of Ottawa

2003-2004 Visiting Worker, National Research Council Canada

2004- Postdoctoral Fellow, Second Language Institute, University of Ottawa

Main Works:

• C. St-Jacques, C. Barrière, and H. Prade, "Fuzzy Logic Tools for Lexical Acquisition," IPMU'2004, Perugia, Italy, Jul. 2004.

Membership in Learned Societies:

• The Canadian Philosophical Association

• Interactive Language Technologies Group (National Research Council Canada)

Name:
Louis-Claude Paquin

Affiliation:
Professor, Communication Department, Université du Québec À Montréal

Address:
C.P. 8888, succ. Centre-ville Montréal (Québec) H3C 3P8 Canada

Brief Biographical History:

1986- Researcher in textual analysis by computer, knowledge representation and expert systems

1994- Professor of interactivity

Main Works:

• L.-C. Paquin, "Machines à contenu et audiovisuel cybernétique," in Interface et sensorialité sous la direction de Louise Poissant Presses de l'Université du Québec, pp. 273-300, 2003.

Membership in Learned Societies:

• Hexagram: Institute for research/creation in Media Arts and Technology (member of scientific committee)

• Centre Interuniversitaire des arts médiatiques (CIAM)