A Case-Based Approach to Adaptive Hypermedia Navigation

Abstract

Hypermedia, with its combination of multimedia and non-linear organization of links among informative nodes, provides a highly interactive environment. In structured domains such as Web-based Educational Systems, the complexity of the learning domain often requires a large set of learning nodes and conceptual interrelationships that can cause sever issues, e.g.: lack of comprehension, disorientation and inefficacious learning strategies. In this paper we propose a new approach to guided navigation in hypermedia-based domains, suitable for helping users in structured and complex learning environments such as cultural heritage domains. Our proposal draws inspiration from case-based reasoning associated with a hypermedia structural analysis. In particular, our presentation highlights the use of a hybrid architecture for adaptive navigation support, where the indexing problem of the case-based reasoner is solved by way of a sub-symbolic approach. A case-study in the Neo-Realist Italian Cinema domain is discussed along with a formal and controlled evaluation that proves the advantages of the proposed approach.

1 Motivations and Goals

Long distance learning via electronic media supplied by a wide range of universities, publishers and other private companies is quickly spreading as an effective way to transfer knowledge and skills to people. Internet, with its vast amount of information and open technologies, is helping developing Web-based Educational Systems (WBES), such as e-learning or Web-based Educational Hypermedia Systems (WBEHS), the most popular tools in this domain.

Several e-learning platforms are available, provided by the open source community, e.g., *Moodle*[1] and *Atutor* [2], or private companies, such as *Blackboard* [3]. E-learning systems offer teachers an environment where they can build their own courses on different knowledge domains, along with learning

[1]http://www.moodle.org

[2]http://www.atutor.ca

[3]http://www.blackboard.com

objects and assessment quizzes. Students acquire information by remote navigating through the learning material. Nevertheless, most of these software environments lack of personalization and adaptation [12] , therefore, they are not able to model students' knowledge and interests in order to adapt the system to their particular needs. WBEHS are basically a set of didactic contents available via browser, e.g., HTML pages, featuring text, still and moving pictures together with sound; data is encoded for rapid access and, typically, the user can explore the available information at will, following links to each component. Paradoxically, the hallmark of such systems, i.e., their ability to put vast amounts of information at users' fingertips, has turned out to be their weak point. It is easy to get lost in hyperspace when the user is navigating through WBEHS of a significant size. Moreover, an excess of information makes hard for the user to find the the the more profitable information to use. With respect to hypermedia systems used as learning aids, users can even loose sight of their objectives (learning a topic, defining a term, etc.) when the system becomes overly complex; they can even feel the frustration of spending more time trying to make the system work than achieving their personal goals. For these reasons, the need for adaptive navigation support has been received much attention from research community, developing several techniques, e.g., direct guidance, link ordering, link hiding, link annotation and link generation (see for example [5] for a review of these techniques).

In this paper we propose a model of adaptive navigation support for WBEHS navigation, particularly suited for educational applications in closed corpus systems, such as Museums Guides [45, 40] and Information kiosks [16], and its implementation in the HyperCase system. The proposed approach is primarily based on the Case-Based Reasoning (CBR) paradigm [34] and on a hypermedia structural analysis. HyperCase offers a series of navigation help tools that can dynamically detect the presumed didactic objective of the user and, if and when needed, subsequently help him/her find the desired path relating to his/her learning aims. The help system is based on a hybrid architecture, consisting of a sub-symbolic module embedded in a case-based reasoner. The type of help offered by the system is displayed to the user by means of a map adaptation technique, based on a hypermedia structural analysis (a slight variation on the proposal in [3]). The project described here is based on a particular philosophy: give the user maximum navigation freedom with the minimum of intrusive help. Thus, the system design specifies that there should be no intervention unless overly requested by the user. Behind this hypermedia philosophy lies our belief in the 'constructivist' view to learning [14, 26, 44] and in the paradigm of "self-directed" education (see, for example, [38]). These ideas contrast with the dogmatic view of "knowledge" and the fundamentally authoritative approach to learning found in highly directive multimedia systems – especially of the educational variety. Hence, our aim was to explore the following research questions, while keeping within the limits of educational hypermedia navigation:

- Can information on prior actions of the user (i.e., on the actions s/he undertakes before the help request is made) serve in attempting to find the presumed learning goal of the user or, at least, to find the aim and corresponding path that can maximize the user's learning, given the partial path already covered?
- How can the system's knowledge of the user's presumed learning goal serve to orient the user?
- What is a suitable, unobtrusive way to display the "advice" given to the user to lead him/her back to the path relating to his/her presumed learning goal?

The domain of interest, chosen as a case study and used for the experimentation of our proposed CBR approach to adaptive hypermedia navigation, is "Italian Neo-Realist Cinema". A preliminary study was performed in order to document the facts, the leading personalities, the films and the themes most relevant to the domain. A controlled experiment was performed to evaluate the system and a non-parametric statistical technique was applied to verify the hypotheses. In our opinion, such a technique is best suited to the evaluation of this type of interactive systems.

Our paper is structured as follows: Section 2 describes the case-based approach proposed for the purposes of guided navigation, with a particular emphasis on the hybrid solution we opted for. Section 3 presents the complete architecture of HyperCase. First of all, we describe the hypermedia system on Italian neo-realist cinema that we developed for the purposes of our experiment. Next, the structural analysis of the hypermedia is presented, along with the map adaptation method, based on the abovementioned analysis by which means the system supplies the requested help to the user. Section 4 focuses on the experimental evaluation of the system, where we report the experimental plan, the statistical method used, the statistical conclusions obtained from the analysis of the data gathered from the experiment and, finally, the research conclusions. Section 5 sets forth a comparison with other related work presented in the literature. The concluding section summarizes our final considerations and briefly touches on possible future developments.

2 Case-Based Navigation Model

Given a WBEHS, the user may be offered different navigation possibilities, the main one being unassisted or free navigation. It is the usual method and involves non-linear access to information contained in the hypermedia nodes without any kind of help or guidance supplied by the system. It is a known fact that, with this navigation modality, users often loose themselves in hyperspace, when the size of the hypermedia becomes significant. Besides, novice users with poor domain knowledge can have problems in dealing with alternative navigation choices and could be best supported by direct guidance technology [5, 9]. One way to overcome this problem is for the system to keep a record of learning goals and the related thematic paths. Thematic paths could be seen as navigation models of "ideal users": each thematic path represents a kind of recommended path for a thorough learning of facts and information regarding a specific topic. At the beginning of the session the user is offered a menu of possible learning goals where s/he may select the specific goal matching his/her interests. At this point, the system could offer an appropriate path in accordance to the user's choice, recommending the selection of such path. However, with this solution, the flexibility of the hypermedia use is reduced, due to the inherent restrictions of this given choice. However, in practice, this approach prevents free navigation within non-linear documents. Instead, in coherence with our constructivist learning vision, we hereby propose a way to use an unobtrusive approach to adaptive navigation support. It allows users to navigate freely in the hypermedia and provides a "help on demand" opportunity. When a user feels lost in hypermedia, the key questions which usually come to mind are: *Where am I?* and *where should I go?* [35]. A valid help system must therefore be able to adequately "answer" these questions. Let us now look into possible responses to the second question *Where should I go?*.[4] For the latter purpose, an unobtrusive system must necessarily try to find the presumed interests of the user exclusively on the basis of the user's actions prior to the request for help. Basically, the only information at its disposal is the partial navigation effected by the user, as the basis for its advice on the best path to follow. It does not have the possibility to "question" users on their preferences and goals. The problem we tackled was therefore: "on the basis of the user's actions prior to the request for help, what advice would a human expert have given, in order to bring the user back on track and allow him/her to fulfill his/her learning aims?". The solution to this problem, as proposed in HyperCase, takes its inspiration from the case-based reasoning paradigm [34]. It involves the use of *retrieve* and *adapt* as a core problem solving model, by means of which we try to "capture" the domain expert's experience in order to put it to the user's disposal.

The reason behind our choice of a CBR approach, rather than other AI methods, was the idea that it would be easier to formalize the knowledge and experience of an expert in the form of cases, rather than using restrictive

[4]The modalities developed to answer the first question *Where am I?*, are treated in the next section.

predetermined models or rules. Specifically, based on a number of sample cases (possible partial paths traveled by users), the expert's advice given to the user in that particular case is recorded and used to resolve new and different cases. This flexible approach is important especially within a field where the expert utilizes, besides a "case database" of past experiences, also talent and skills that are very difficult to formalize, what we often call "intuition". Therefore, the first step involved the development of the "case" representation. As can be deduced from the preceding paragraphs, a case that generally has a $<$*problem representation*, *solution*$>$ structure, must instead be given a $<$*partial path representation*, *offered user help*$>$ structure in HyperCase. The partial user path could be represented by way of a path (sequence of nodes and arcs) in the graph representing the hypermedia [39]. We believe, however, that such representation would not offer a practical management of somewhat frequent and frustrating phenomena, such as "chaotic navigation", attempted access to various nodes linked to the current one, etc.. We instead formulated a simpler hypothesis, to be further verified experimentally, which consists in representing the user's actions by taking into consideration only those nodes visited during his/her partial navigation (thus ignoring the links that are in any event predefined within hypermedia) and the user's elapsed time on each node, including the current node, i.e. the one where s/he is located when the call for help is made. In this way, we represent the user's actions simply by means of a pattern, consisting of an array of $n + 1$ components, where n is the number of nodes forming the hypermedia. The first n elements of the array record the elapsed times, i.e., the times t_i the user has spent on each node n_i (t_i is obviously equal to zero for unvisited nodes), while the last element represents the current node. Basically, this alternative means that the problem of knowing the user's presumed learning goal is redirected to a problem of *pattern recognition*. In a preliminary phase a high number of partial paths obtained from real users were considered and submitted to the domain expert. For each given partial path, the expert determined, on the basis of his/her experience and knowledge, the kind of advice to be given to the user, developed in consideration of the learning goal to be recommended and the corresponding thematic path to follow. The expert also supplied, for each partial path, an ordered list of learning goals and correspondent thematic paths of possible interest to the user. The number of "cases" thus determined was subsequently increased, again under the supervision of the expert, through a "perturbation" process in respect to the given partial paths, which entailed slight changes to the paths, without however altering the corresponding "solution" to the case.

All this allowed us to obtain a sizeable variety of cases (about $8,000$). At this point, the CBR approach would entail the construction of the "library of cases" and the definition of a metric for the retrieval of the closest matching old case to the new partial path from such library (the *new problem*

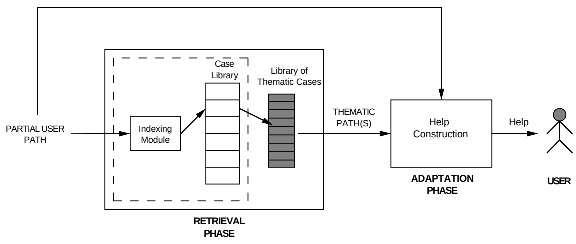

Figure 1: Case-Based Navigation Model.

in CBR terms), to respond to help requests. The retrieved old case would supply the kind of help to be used to assist the user. It is nevertheless obvious that this approach entails the definition of an adequate metric for the retrieval phase. This is not an easy task, because this retrieval mechanism must work even when there is "noise" in the pattern (unforeseen variations of the elapsed times, nodes visited "just to see where it goes", etc.), i.e., in the new partial path to be processed. Instead, the method we used in HyperCase considers the actual construction procedure of the help requested at the time as the "old case solution". It does not involve the off-line construction of the "help" of the old case. The construction procedure requires as input the partial path and the thematic path (related to the learning goal) suggested by the old case.[5] This choice would therefore result in a situation as illustrated in Figure 1, where the old cases have a structure of a <*partial path representation*, *thematic path*> type, where the field *thematic path* is actually a pointer to a new library, which we could name a Library of Thematic Cases, containing the various thematic paths together with the corresponding learning goals. The solution of the old case would be obtained by activating the help construction procedure, a procedure that would obviously be external to the case library.

This last design choice, together with the one presented earlier, relating to the representation of the user's actions as a pattern, allows the possibility to implement the box represented in dashed lines in Figure 1, as an artificial neural network, functionally equivalent to the afore-mentioned box. The old cases in the case library were utilized as training records to train the network that, in this way, provides a "monolithic" representation of the knowledge in the case library. This monolithic knowledge representation, or lack of transparency, that is generally seen as a weak point of artificial neural networks, is not prejudicial in our case. In fact, as fully illustrated in Figure 1, it is not necessary to check inside the case library (the old retrieved case) to find the solution, but it is simply enough to know the pointer to the Library of Thematic Cases and to activate the procedure by

[5]An accurate description of the above procedure, i.e., of how our system constructs the "advice" to the user by means of a graphic representation, is given in Section 3.3.

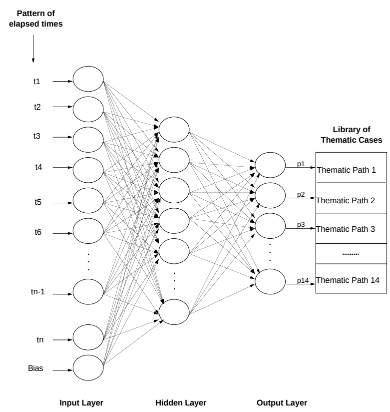

Figure 2: The Artificial Neural Network.

providing the thematic path discerned by the old case and the effected partial path. The latter process is the *adaptation* phase of the old case to the "new problem". A result of this choice is that the metric of the retrieval module in Figure 1 is replaced by the generalization ability of the neural network. Furthermore, this way the project gains an added value of low sensitivity to noise, as neural networks generally tolerate noise in input data relatively well. Figure 2 shows the employed artificial neural network, involving a Multi-Layer Perceptron [22] that is well suited to classification problems that are not *linearly separable*. The network consists of three layers. The first layer involves $n + 1$ neurons (in addition to one neuron per bias) that are given the pattern that describes the user's partial path. The time t_i spent on each hypermedia node is expressed by way of a value ranging from 0 to 1, effected as a normalization of the time limit (fixed by the expert) equivalent to a reasonable amount of time that a user may spend on a node. If the user spends more time than expected on a specific node, the value of the corresponding input node would in any event be maintained equal to 1. Basically, a "saturation" of elapsed times on the hypermedia nodes has been envisaged, in order to avoid interference of a "coffee break" kind, etc., which may occur during a working session. The output layer comprises as many neurons as the learning goals and corresponding thematic paths foreseen for the hypermedia, i.e., 14. The network thus provides as output a rank-ordered list of thematic paths. As far as the hidden layer is concerned, several tests were made by training the networks with different configurations as to establish the most suitable number. The Backpropagation [22] algorithm was used for the network training. A set of $6,000$ cases was utilized for the training purposes (the other $2,000$ were used for the validation phase). About $40,000$ training epochs for various configurations of hidden neurons were made. The best configuration was the one with 15 hidden neurons, which gave the lowest RMSE value (< 0.06) and the highest success rate

(99.6%) during the test phase, and was consequently applied in our system.

3 The Architecture of HyperCase

The general architecture of the HyperCase system has four main components: the *Retrieval Module*, the *Library of Thematic Cases*, the *Help Module*, the *User Interface*) During a navigation session, the user may freely navigate in the hypermedia, and ask for help whenever s/he feels the need for navigation assistance. This request is processed by the *Retrieval Module* that, as illustrated in the previous section, tries to find the presumed learning goal of the user and consequently the thematic path to be followed. At this point, the *Help Module* is activated and, on the basis of the found learning goals and corresponding thematic paths, it seeks the most appropriate advice for the user. The advice that the system provides to the user is represented in tree-shape graphic form, constructed on the basis of a structural analysis of the hypermedia. The following Section is devoted to the description of the actual hypermedia we have built to experiment our proposed CBR approach to guided hypermedia navigation.

3.1 The Domain of the System

The domain chosen by us to realize and experiment the proposed CBR approach for guided navigation is the Italian neo-realist period. A film critic has also been involved in the project, as the domain expert and educational expert.

This domain is surely interesting, but not easily explorable because the relationship between facts, persons and films, protagonists of the period under review, are not readily ordered into 'known' paths. In fact, there exist few filings on the topic, and the assignment of a film to the neo-realist period may be subject to controversy and personal judgment, since critics rarely offer unanimous opinions [4]. The neo-realist period was a very particular time for Italian cinema, more or less situated between 1945 and 1952, even if it is difficult to pinpoint precise temporal boundaries for such fields.

With the help of the domain expert, we selected the four main directors of the neo-realist period and, most important, their respective films. We thus considered the features directed by *Rossellini*, *De Sica*, *Visconti* and *De Santis*, who truly marked the course of the neo-realist movement. Furthermore, our selection expanded to include all the directors who took inspiration from neo-realist aspects or who gave a particular imprint to neo-realist ideas, as, for example *Blasetti*, *Castellani*, *Germi*, *Rosi*, *Lizzani*, etc. In addition to these individuals, some of their films were obviously also considered and, just as significant in consideration of the educational scope of the hypermedia, a number of themes common to the films under review were also included in our project.

Figure 3: An Exerpt of the Node "Roma Città Aperta" with an overview of the movie and suggestions on related information the user may be interested.

With regard to the development of the hypermedia, we took advantage of the HDM model (see [20]), assessed the different types of topic groups involved (*films*, *directors*, *scriptwriters*, *themes*) and developed a system involving approximately 80 nodes and about 500 links. The size of this system, albeit somewhat limited, is nevertheless enough to provoke navigation disorientation phenomena and was consequently suitable for our experimentation purposes. In any event, as pointed out in [6], didactic hypermedia are typically of a limited size, especially if compared to the extent of other hypermedia applications, as for example "Information Retrieval Hypermedia" or "On-Line Information Systems".

As an example, let's review the components of the *film* topic group. Figure 3 shows parts of the "hypermedia node" relating to Rossellini's film "Roma Città Aperta". Besides common sections such as: reviews, technical file card, plot, trivia, photos; the page offers also related navigation paths to the visitors.

We have already mentioned the work performed with the domain expert for the selection of common themes shared by the films under consideration; this analysis resulted in the selection of 14 possible "thematic paths". Some of these have been entitled as follows: *Rome in the neo-realist period*, *The difficult post-war period*, *The wings of neo-realism*, *Standing by the silent people (women and children).*

3.2 Structure and Metrics of the Hypermedia

In accordance with [3, 10, 37], a first practical way of helping a user is by producing a structure for the Hypermedia and mapping the user's location inside this structure. A suitable kind of structure for such purpose would have a hierarchical organization [1]. In order to construct this type of structure it is necessary to select a specific hypermedia node to be used as the structure's root. For such purpose, we extended the scope of the proposal of [3, 35], as described here below.

Let's consider the graph representing the hypermedia. Given the distance matrix M of the graph, we can define the *Converted Distance Matrix* C as follows:

$$C_{i,j} = M_{i,j} \quad \text{if} \quad M_{i,j} \neq \infty$$

$$C_{i,j} = K \qquad \text{if} \quad M_{i,j} = \infty$$

being $K = n$ (where n is the number of nodes in the graph). We can then define the following parameters:

$$COD_i = \sum_{j=1}^{n} C_{i,j}$$

The COD_i parameter gives a good indication of the topological centrality of the node i in the hypermedia.

The *Converted Distance* CD of the whole hypermedia is given by the sum of all the elements of the *Converted Distance Matrix* C:

$$CD = \sum_{i=1}^{n} \sum_{j=1}^{n} C_{i,j}$$

This parameter gives indications on the general connection of the graph.

The *Relative Out Centrality* ROC_i of a node i is defined as the normalization of COD_i on the entire hypermedia:

$$ROC_i = \frac{COD_i}{CD}$$

A high ROC_i parameter indicates a node i from where the other nodes of the graph may be easily reached.

The previous metric is related to the topological properties of the graph. These may be seen as syntactic properties, as they do not take into consideration the content of the various nodes. We added another parameter to the previous representation relating to the thematic relevance of each node in the hypermedia and found a metric to determine such relevance. We define the thematic relevance of a node as the *Thematic Multiplicity* TM_i of the node inside the thematic paths, i.e., the number of thematic paths that contain the node, normalized on all thematic paths:

$$TM_i = \frac{M_i}{TP}$$

being M_i the multiplicity of the node i in all the thematic paths and TP the number of thematic paths. TM_i is a good indicator of the importance of the node for the fulfillment of the various learning goals. We did not normalize it on the total number of nodes n because we assume that the thematic relevance of a node does not depend on the size of the graph.

Now, in order to balance the thematic relevance with the syntactic one with respect to the entire graph, we performed the following normalization giving the same average:

$$\frac{\sum_{i=1}^{n} ROC_i}{n} = \beta \frac{\sum_{i=1}^{n} TM_i}{n} \quad \Rightarrow \quad \beta = \frac{\sum_{i=1}^{n} ROC_i}{\sum_{i=1}^{n} TM_i}$$

Hence we get the normalization factor β.

We subsequently defined the GW_i parameter, *Global Weight* of a node i, as the sum of the preceding parameters:

$$GW_i = ROC_i + \beta \cdot TM_i$$

The parameter GW_i gives indications on the global relevance of a node inside the graph.

3.3 The Help Module

The help module is able to supply different types of help to users, by providing graphical representations on the basis of a metric defined in the previous section. It answers the typical questions raised by disoriented users [33], i.e.:

- *Where am I?* In solving this dilemma, the system supplies a tree representation mapping the user's location.
- *Where should I go?* This is the kind of help where the contributions of Artificial Intelligence methods are more evident. The system shows a tree that maps out the steps the user should take in order to return to the most relevant thematic path.
- *Were was I?* For sake of completeness, the system is capable of supplying the rank-ordered list of nodes visited by the user during the current session.

We shall now describe the kinds of help *Where am I?* and *Where should I go?*. As concerns the construction of the hierarchical tree *Where am I?*, the most delicate aspect involves the choice of which node to use as root. In fact, once the root node is chosen, the hierarchical tree is built automatically, through a *bredth first* technique applied to the hypermedia graph. The chosen node must possess several important characteristics: it must be a crossing point from where all nodes (or nearly all) may be reached, it must be within reasonable reach from any other node, it must have a reasonable amount of descendent nodes. Rivlin *et al.* [35] propose as candidates those nodes with the highest *ROC* parameter. Instead, for our project, we opted to chose the node with the highest *GW* parameter. Indeed, such metric, in addition to the qualities given by *ROC*, also measures the "thematic" importance of the node. Once the root is selected and the hierarchical tree is built, we must then deal with the appearance problem. It is practically impossible and fundamentally useless to display the whole tree, because otherwise the user would be submerged by an excess of information. We decided to provide a *fisheye* view of the hierarchical tree. To develop this kind of image, we defined a "Degree Of Interest" function (DOI) for the various nodes. This function assigns a value to each node, in accordance with the user's interest in viewing that particular node. The DOI function for a node x, assuming that the user is on the node y, is defined as follows:

$$DOI(x/y) = API(x) - D(x, y)$$

where $API(x)$ is a global a priori evaluation of the importance of the node x, and $D(x, y)$ is the distance between x and y. The fisheye view is created by fixing a threshold k and showing only those nodes with a DOI function above the predetermined threshold. In accordance with [19], it was decided to put The $D(x, y)$ corresponds to to the length of the path (in the input hierarchical tree) that joins node x to node y. Similarly, $API(x)$ is made equivalent to the distance of the x node from the tree's root. At this point, it is sufficient to establish a threshold k and show only the nodes where $DOI(x) \geq k$. We decided to put k to the DOI value of the offspring of the current node, obtaining a *first order* fisheye view of the tree. Again, for sake of clarity and visual impact, only the structural links are displayed. However, even the reference links output from the current nodes are shown, although not using lines as it is the case for structural links, but by giving an active property to the icons and the titles of the target nodes of the reference links. In this way, all the nodes that can be reached from the user's current location are active (meaning that they can be clicked to access their content), while unreachable ones are not.

The algorithm we implemented directly produces the tree to be displayed (meaning that the hierarchical tree and the fisheye view are developed at the same time) and is informally described as follows:

1. The shortest path between the root and the current node is calculated.
2. The root and all its offspring are displayed.
3. The descendent of the root belonging to the shortest path calculated in step 1 is expanded; in other words all the immediate descendents of this node are displayed thus avoiding visualization of already shown nodes. The offspring of the root that belongs to the previously computed shortest path is expanded, i.e., all the descendents of the node are displayed except for those nodes that have already been visualized.
4. The procedure continues by expanding all the nodes of the shortest path until the current node is reached.
5. Finally, the current node is expanded.

To further exemplify the above ideas, we can refer to the simple graph example shown in Figure 4, assuming that the user is located on node *A*.

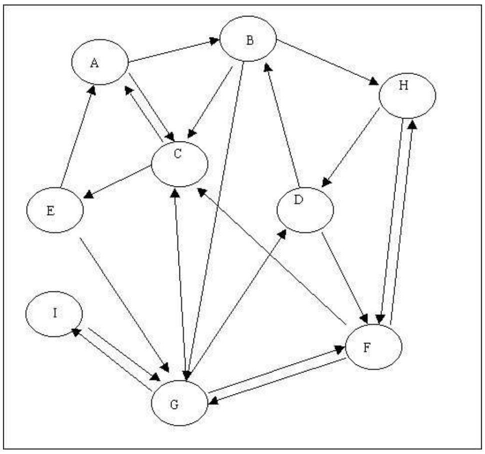

Figure 4: A Simple Example Graph.

Figure 5 shows the hierarchical tree, however in this case node B has been chosen as the root as it has the highest *GW* parameter . Instead, Figure 6 depicts the *fisheye* tree, built following the algorithm illustrated earlier.

Figure 7 presents a snapshot example of the tree as effectively displayed by our system when the *Where am I?* help request is made.

We shall now illustrate how the system answers to the question *Where should I go?*. In this case the system considers the thematic path with the highest priority rating, and supplies a recommendation to the user, assuming that the user is truly interested in such path/destination. The ordered list of paths is in any event made available to the user, who may even select the

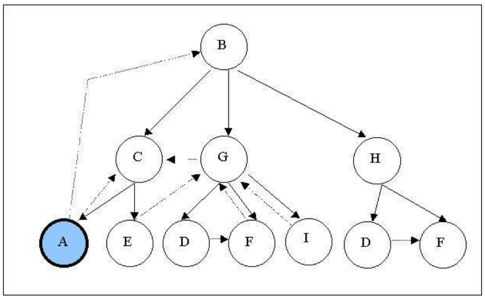

Figure 5: The Hierarchical Tree for the Example Graph.

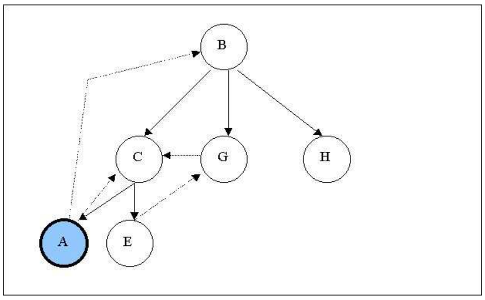

Figure 6: The Fisheye View of the Tree for the Example Graph (first modality).

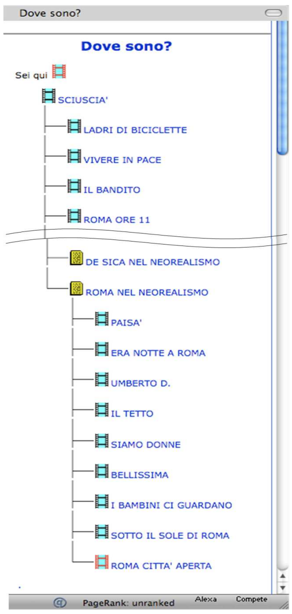

Figure 7: The Help for the Question *Where am I?*.

lowest path on the list if s/he believes that his/her interest does not coincide with the paths given a higher priority. For example, the user may deem the second ranking path to be the most appropriate one and therefore chose to select it; in this case the help module will adapt its data in accordance to this preference. If the user is located on a node belonging to the given thematic path, the suggestion given to him/her is obviously to move to the next node belonging to that path. If the user is located on a node that does not belong to the thematic path, the system first suggests a return to the last visited node of the respective thematic path and, upon the user's return, recommends a move to the next node of that path. This advice is expressed both in textual and graphic form by way of a small tree where the root is the last node of the thematic path visited by the user. The suggested path/nodes are shown in a different window of the browser.

4 Experimental Evaluation

Our experimental evaluation has been organized into those phases typical of an investigation in the behavioral field, but adjusted for the Web-based adaptive hypermedia field, and our observation focused on the correlation between the kind of help provided by the system in its different forms, the different navigation modalities and the user learning process.

For a better and more extensive exploration of the research questions mentioned in Section 1, our experiment included three different navigation modalities, each dependent on the particular help modality applied. The three modalities foreseen are as follows:

1. Modality $\mathcal{A}$: it corresponds to free navigation, where the user receives no help whatsoever from the system.

2. Modality $\mathcal{B}$: it corresponds to navigation with the *static* help module. The system answers the questions *Where was I?* and *Where am I?* in accordance to the modalities described in the previous section, without utilizing the AI component.

3. Modality $\mathcal{C}$: it is the most complete modality, as it includes the AI component. It corresponds to navigation with the *dynamic* help module, i.e., it can answer the question *Where Should I go?* in addition to the *Where was I?* and *Where am I?* questions (covered by the $\mathcal{B}$ modality) by using the recommended thematic path as determined by the system.

Obviously, once the navigation modalities $\mathcal{A}$, $\mathcal{B}$ and $\mathcal{C}$ have been identified, it is necessary to clarify how the "user learning" process is measured. In statistical terms a stochastic variable $\mathcal{L}$ = *user learning* needs to be defined for measurement purposes. To this end, a post-navigation test was submitted to all the users involved in the investigation immediately after their respective navigation. The questionnaire consisted of multiple choice and fill-in-the-answer questions. This test was developed by the domain expert to measure the amount of knowledge acquired in connection to the different navigation modalities used, i.e., $\mathcal{A}$, $\mathcal{B}$ or $\mathcal{C}$. To answer this question, we defined the random variable $\mathcal{L}$ as the *score in the post-navigation test*, i.e., as the expression of the level of knowledge acquired by the users, on the basis of the indications given by the domain expert. The use of tests for the measurement of learning processes is moreover a widespread practice in educational systems in general [15, 30]. Therefore, the experiment we carried out aimed to effect the following comparative evaluations:

1. Does the user navigating with modality $\mathcal{B}$ have an increased learning ability compared to the user modality $\mathcal{A}$?

2. Does the user navigating with modality $\mathcal{C}$ have an increased learning ability compared to the user modality $\mathcal{A}$?

3. Does the user navigating with modality $\mathcal{C}$ have an increased learning ability compared to the user modality $\mathcal{B}$?

As concerns the work plan, we initially formulated the *statistical questions* concerning the statistical model to be adopted, such as the *Hypothesis Testing* and the *Interval Estimation techniques*. Next, we carried out the investigation and subsequently analyzed the *statistical conclusions* that determined the acceptance or rejection of the null hypotheses concerning the different navigation modalities used in our investigation. Finally, we worked out the *research conclusions*, i.e., the answers to our initial questions representing the goals of this research.

4.1 The choice of the Statistical Model

The statistical test has been selected according to the following criteria: (i) it needs to be non-parametric as not to force the normality of the distribution of the involved populations; (ii) it must be able to perform the *Hypothesis Testing* on independent samples, as it is the case of groups of users who navigate according to the different modalities $\mathcal{A}$, $\mathcal{B}$ and $\mathcal{C}$; (iii) it must be applicable to small samples, such as groups of users involved in the current investigation. In particular, it must ensure, with a predetermined low margin of error (significance level α), that the differences found in the post-navigation test between two groups of users, who navigated according to different modalities, are effectively due to the distinct situations they faced, i.e., to the different kind of help used during the navigation. In more strictly statistical terms, we verify whether the statistical distributions involving the random variable $\mathcal{L}$ = *score in the post-navigation test* to which the populations yielding the samples belong, differ only because of a translation $\Delta > 0$. Hence the effect of the *treatment* of the user can only be a translation towards higher values of the random variable $\mathcal{L}$, i.e., a simple additive effect. Next, it is important to assess such a difference Δ by means of both a calculated estimation as well as an *Interval Estimation* technique. In consideration of the above, we have chosen the Wilcoxon-Mann-Whitney test (WMW) [42] for two independent samples based on sums of ranks. This test appears to be more effective than the similar *Student t test* [23] for small samples and non-normal distributions. Finally, by means of the Hodges and Lehmann procedure [24], it has been possible to estimate the confidence interval related to the difference Δ.

4.2 The Statistical Questions

The following *Statistical Questions* are inferred, one for each comparative evaluation mentioned in Section 4 and from the considerations regarding the choice of the statistical model set forth in the previous Subsection.

- *Question* 1*:*

  Null Hypothesis H_0*:* The differences observed in the measures of the statistical parameters for the two samples that navigated according to modalities $\mathcal{A}$ and $\mathcal{B}$, are due to chance and the two groups of users belong to the same statistical population.

  Alternative Hypothesis H_1*:* The population yielding the sample that navigated according to modality $\mathcal{B}$, is different from the population yielding the sample that navigated according to modality $\mathcal{A}$.

  In statistical terms: H_0: $\theta_{\mathcal{B}} = \theta_{\mathcal{A}}$ and H_1: $\theta_{\mathcal{B}} > \theta_{\mathcal{A}}$, being $\theta_{\mathcal{A}}$ and $\theta_{\mathcal{B}}$ respectively the medians of the statistical distributions $\mathcal{L}_{\mathcal{A}}$ and $\mathcal{L}_{\mathcal{B}}$ to which the stochastic variable $\mathcal{L}$ belongs.

- *Question* 2*:*

  Null Hypothesis H_0*:* The differences observed in the measures of the statistical parameters of the two samples of users who navigated according to modalities $\mathcal{A}$ and $\mathcal{C}$, are due to chance and the two groups of users belong to the same population.

  Alternative Hypothesis H_1*:* The population yielding the sample that navigated according to modality $\mathcal{C}$, is different from the population that navigated according to modality $\mathcal{A}$.

  Hence, in statistical terms: H_0: $\theta_{\mathcal{C}} = \theta_{\mathcal{A}}$ and H_1: $\theta_{\mathcal{C}} > \theta_{\mathcal{A}}$, being $\theta_{\mathcal{C}}$ and $\theta_{\mathcal{A}}$ respectively the medians of the statistical distributions $\mathcal{L}_{\mathcal{A}}$ and $\mathcal{L}_{\mathcal{C}}$ to which the stochastic variable $\mathcal{L}$ belongs.

- *Question* 3*:*

Table 1: Wilcoxon Test Results.

Comparison	$p - value$	H_0	$\widehat{\Delta}$	$[\alpha, \beta]$
1 ($\mathcal{A}$ vs. $\mathcal{B}$)	0.036	Rejected	$\widehat{\Delta}_1 = 25$	$[0, 44]$
2 ($\mathcal{B}$ vs. $\mathcal{C}$)	0.027	Rejected	$\widehat{\Delta}_2 = 35$	$[0, 67]$
3 ($\mathcal{A}$ vs. $\mathcal{C}$)	0.001	Rejected	$\widehat{\Delta}_3 = 65$	$[14, 78]$

Null Hypothesis H_0*:* The differences observed in the measures of the statistical parameters of the two samples that navigated according to modalities $\mathcal{B}$ and $\mathcal{C}$, are due to chance and the two groups of users belong to the same population.

Alternative Hypothesis H_1*:* The population yielding the sample that navigated according to modality $\mathcal{C}$, is different from the population that navigated according to modality $\mathcal{B}$.

In statistical terms: H_0: $\theta_{\mathcal{C}} = \theta_{\mathcal{B}}$ and H_1: $\theta_{\mathcal{C}} > \theta_{\mathcal{B}}$, being $\theta_{\mathcal{C}}$ and $\theta_{\mathcal{B}}$ respectively the medians of the statistical distributions $\mathcal{L}_{\mathcal{B}}$ and $\mathcal{L}_{\mathcal{C}}$ to which the stochastic variable $\mathcal{L}$ belongs.

4.3 The Statistical Sample

For our experiment, we formed a sample of 21 users, with an homogeneous starting knowledge on the domain of interest. Within this group, 7 users navigated according to modality $\mathcal{A}$, 7 according to modality $\mathcal{B}$ and 7 according to modality $\mathcal{C}$ for a total of 120 minutes each.

4.4 Hypothesis Testing

In this Subsection we report in Table 1 the WMW test results, together with the results for the confidence interval of the variable Δ, obtained by means of the Hodges and Lehmann procedure [24], with a level of significance $\alpha = 0.05$.

4.5 Discussion

The statistical results obtained by means of the WMW test are summarized in Table 1, where the first column shows the tested comparisons. In all cases we obtained: $p - value < \alpha$. Consequently, we must reject all the null

Table 2: Comparison among $\mathcal{A}$, $\mathcal{B}$ and $\mathcal{C}$ Navigation Modalities.

Comparison	*Ratio*	*Added value*
$\mathcal{B}$ vs. $\mathcal{A}$	$\frac{\theta_B}{\theta_A} = \frac{60}{35} = 1.71$	71%
$\mathcal{C}$ vs. $\mathcal{B}$	$\frac{\theta_C}{\theta_B} = \frac{100}{60} = 1.66$	66%
$\mathcal{C}$ vs. $\mathcal{A}$	$\frac{\theta_C}{\theta_A} = \frac{100}{35} = 2.85$	185%

hypothesis H_0. This means that after navigating, the three samples of users belong to different distributions from the original ones due to a translation estimated to be towards higher values. The estimated translation $\widehat{\Delta}$, shown in the fourth column needs to be considered: it is different in all three WMW tests. Table 1 highlights that the translation, estimated in an exact way for the testing of hypothesis 1 was: $\widehat{\Delta} = 25$, whereas it was $\widehat{\Delta} = 35$ in the case of testing hypothesis 2 and finally it was $\widehat{\Delta} = 65$ for the testing of hypothesis 3. These scores undoubtedly strengthen the alternative hypotheses H_1. The last column of Table 1 shows the results obtained by means of the Hodges and Leeheman procedure applied to the samples, for the confidence interval estimation of $\widehat{\Delta}$ at 95%. In fact, the last column of Table 1 shows the lowest and the highest values for the distribution translation due to the navigation.

As already stated in the previous section, it turns out that all the three null hypotheses must be rejected. This supports all three of our alternative hypotheses, because in all three cases we have: $p - value < \alpha = 0.05$. The sample navigating according to modality $\mathcal{C}$ is very different from sample $\mathcal{A}$. In addition, modality $\mathcal{B}$ is between modalities $\mathcal{A}$ and $\mathcal{C}$. This is meaningful because it implies that even when the topological and semantic orientation provided by the system is static, i.e., maintaining the same node as root, (higher GW parameter), it nevertheless promotes the learning process by means of a less chaotic and a more guided navigation. If we want to estimate the added value provided by the two types of help, static (modality $\mathcal{B}$) and dynamic (modality $\mathcal{C}$), compared to the navigation performed without any type of help, we must first compute the statistical parameters of the three samples, i.e., their Median θ.

We can thus express the estimated added value by computing the ratios between the modalities, i.e., the ratios between the Medians of the shifted statistical distributions. The results are shown in Table 2.

As we can see from the last column of Table 2, the added value of the navigation, effected by means of the "intelligent help" module is well-evident: it can be up to 185% higher than the value obtained from a non-assisted navigation and 71% higher than the one drawn from a navigation with a static, topological-oriented help module.

The inferential statistical model based on a non-parametric hypothesis testing, calculated on the score obtained in the output test, confirmed the correlation in its different combinations, at different levels. In particular, it strengthens the hypothesis that the proposed adaptive help, obtained by way of AI techniques, will effectively find the learning goal of the user or, at least, the related aim and thematic path best suited to the user's learning purposes. Moreover, the knowledge that HyperCase infers about the user's learning goal is of great advantage to user disorientation problems, since it enables the construction of the most appropriate help service to bring the user 'back on track'.

5 Related Work

We shall now present an overview of some of the more significant proposals regarding adaptive educational hypermedia, developed during past years in order to face the disorientation problem of navigation in closed-corpus hypermedia domains, such as guided tours in museums, galleries or monuments or cultural heritage information. In particular, we will focus on approaches based on adaptive navigation, that is, the manipulation of links that are presented within pages [6].

The reader is referred to [29, 7, 8] for a more in depth description of the various adaptive hypermedia systems proposed in the literature.

In [18], Funk and Conlan study how feedback helps authoring and improves personalization in a education environment. The feedback may be gathered implicitly by analysis and evaluation of the learner's progress, or requested explicitly from the user. The learning content may be structured at runtime in different ways, e.g. text documents, slides, animation, simulation, interactive, etc, according to the learner preferences. Clustering techniques group learners with similar preferences and needs into sets of stereotypes. This is particular useful when the learner models are sparse and incomplete. A case-based reasoner is employed to sequence learning objects by means of required competence and additional competence achieved according to prerequisite requirements, in terms of knowledge or competencies the learner is supposed to have. The work does not provide details on the implementation or any evaluation.

Fink *et al.* [28, 25] focus on adapting hypermedia for elderly and disabled users. User models are acquired through interviews, inference and stereotypes and are hierarchically organized including the respective handicap and the ability to use complex user interfaces. The adaptivity is mostly based on stereotypes of users with similar handicaps, simplifying the GUI according to the abilities of current users and suggesting information related to their needs. The evaluation involves a small group of users and does not include a formal empirical methodology to prove the efficacy.

From a different prospective, Interbook [36] provides guided tours in form of tables of contents organizing the most relevant subset of the material to the user through conceptual networks. Each link between learning objects is tagged with one the following educational states: ready to be learnt, recommended, not ready to be learnt. Interbook is based on the domain modelling approach of ELM-ART [41], an intelligent interactive educational system that supports teaching of programming languages. In order to sequence the available content, the system provides adaptive navigation support in terms of suggested links connected to the most relevant next unit for the current user. Each learning unit is represented as an object containing text unit and information that can be used to relate units and concepts to each other. The learners are evaluated with tests, i.e. a sequence of questions that examine the knowledge of the user about the concepts explained in that unit. The effectiveness of Interbook is yet to be evaluated, while the evaluation of the user knowledge based on explicit tests does not suggest a feasible adaptation of ELM-ART in our domains.

Further systems in literature follow different approaches. Exploiting the Web to deliver information to different devices is the goal of the system described in [43]. A discourse planner with a Web query and document synthesis technology answer user queries generating hypertext that is appropriate to the desired medium for delivery. The described adaptivity is location-dependent. The same adaptivity is used in the GUIDE project [11], where personal context, i.e., current location, preferred reading language, etc. is used to tailor the information presented to the visitor The domain representation allows of seting relationships between informative objects in order to determine optimal routes between attractions. Special tags in HTML pages are replaced with personalized information.

The NAUTILUS architecture [21] consists of user profile updated by relevance feedback provided by the users. The users profiles are employed to perform a focused autonomous navigation by following only the hyperlinks that were evaluated as more promising. A Java graphical interface provides the NAUTILUS recommendations to the user. User profiles are built by means of TFxIDF and expected information gain. Recursive neural networks are employed to score and recommend links. A collaborative approach is employed by Bollen [2] generates navigation path based recommendations for individual users according to group user models.

A further work [31] aims to design a virtual assistant for museums. Users are supported, during their visit, by a virtual guide using techniques such as user stereotypes (tourist, student, expert) or models derived from user preferences. At the beginning, user needs can be explicitly indicated among a set of predefined options, and they can be updated during a session taking into account the user accesses. The system suggest various kinds of information, such as summaries, comparison and difference information related to the current page. Nevertheless, it does not provide any adaptivity about the organization and sequencing of the available informative units.

Kadobayashi *et al.* [27] allows users to explicitily express interest on a set of topics. Then, using a predefined network that associates the topic according to their semantic closeness, a mediating agent identifies further new information that can be interesting for users.

Finally, the AHA! system [13] uses link hiding and annotation techniques in order to help students to learn the proposed knowledge domain. This system, designed as a generic adaptive hypermedia system, offers adaptive content through fragment variants and adaptive link presentation through link annotation, link hiding and/or link removal. The AHA! system allows AHS authors to define new concept relationships types in order to be a multi-domain AH authoring system as well. The system records, for each user, the visited nodes and, by means of pre-set rules suggests the next node to visit. Differently, our system was designed to run on closed and complex domains in order to be more effective in helping users to not loose in hyperspace. HyperCase records fir each user the visited nodes along with the fruition time and the node where the user currently is. In our system the pre-set rules are the thematic paths.

6 Conclusions and Future Work

Our contribution is focused on an approach based on cases for guided navigation in hypermedia environment and its application within the HyperCase system, particularly tailored for educational purposes.

The main idea of the proposed approach lies in the attempt to automatically deduce users' learning goals and subsequently supply the relevant guidance for their hypermedia navigation. The interaction process with the system is based on our constructivist and self-directed learning vision. The idea has taken the practical form of a completely unobtrusive help system, where the system 'steps in' only at the user's specific request. An experimental evaluation with non-parametric statistics techniques shows evidence in the effectiveness of the proposed system.

The adaptive hypermedia system is well designed for closed-corpus that can be manually tagged by an expert but it is not easily scalable to more wider domains such as the Web. To reach this target, new techniques able to recognize abstract goals on the basis of user actions and automatically retrieve and organize learning paths must be developed. Thanks to these techniques, the domain expert is not longer required and the CBR approach may be successfully applied in the every-day user task.

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