Traffic Architecture Driven Organization and Visualization of Learning Objects Metadata in Virtual Environment

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Abstract

We are building a Learning Object Metadata (LOM) [1] organization and presentation prototype where topics of interest can be retrieved from any information repository [14]. This paper introduces a structuring method applied to the accumulated search results. First the frequency and rank of the search keywords are calculated and therefore the result is partitioned and grouped under the most ranked keywords. The ranked keywords are taken further into consideration for finding semantics and approximating relation metrics that would allow us to cluster the groups. A highway metaphor has been introduced to navigate the clusters presented as road like segmentation unit over the 3D virtual landscape. Since the groups are connected with the other groups using the road network and according to the relation metrics, it would surely increase the navigation experience of the user to search for the topic of interest. Although evaluation of the effect of the novel road networked highway metaphor and the user study on the prototype is yet to be done, we have found the metaphor intuitive and entertaining while searching for the pattern and relation in the presented information.

1. Introduction

Information visualization is a popular and advancing field of study that is defined as the use of computer-supported, interactive, visual representations of abstract data to amplify the user's cognition [6]. The limitation of memory and perceptual ability of the human brain makes it difficult to relate huge amounts of information with each other. Information visualization schemes assist in building an interactive construct that establishes a relation between the user and the knowledge stored in the computer. Graphs or charts are more popular to aid in understanding progress or determining relations than to real or abstract numerical information [13], [5]. It is evident that the brain's computational ability prefers the visual representation of a system rather than its written description as it influences the cognitive ability of humans [4]. However, the transfer of knowledge to learners understanding is challenging and difficult to manage because of the trade off between the overview and the details that are needed to be communicated.

Appropriate information visualization tools [6],[18] and [8], are needed to be addressed for efficient data presentation. To facilitate the information transformation process, we have adopted a 3D visualization scheme [16], which uses a 3D spatial layout. The layout provides an attractive, large display space as well as natural and cognitive aspects of visualizing more information at a time [7]. Furthermore, a visually organized representation of the information allows the users to get insight into the data, directly interact with it, draw conclusions, and come up with new hypotheses. Its target is to not only reinforce the traditional presentation concept but to also open up multiple avenues to foster a greater understanding of the information presented, enhancing learning based on preferences and learning contexts. Finally, the 3D metaphor has been augmented with a game-like environment to bring attractions to the searching and learning process.

The remainder of this paper is arranged as follows. Section 2 presents a general overview of the semantic road network construction framework. In Section 3.1, we specify the theorems and methods that are needed to cluster the information. This is followed by Section 3.2 where we describe the segmentation creation algorithm for the representation of the information in the 3D environment. The implementation details and the result study are covered in Section 4. The conclusion and future work are presented at the end.

2. Overview

The use of visual metaphors is effective for the transfer of knowledge [15]. Eppler [12] has mentioned, there are six advantages of using metaphors: (i) to motivate people, (ii) to present new perspectives, (iii) to increase remembrance, (iv) to support the process of learning, (v) to focus the attention of the viewer and (6) to structure and coordinate communication. To adhere to the hypothesis, we have designed our 3D highway metaphor prototype with a game like interface in order to promote entertainment and comfort in the learning process. New users will find it easy to navigate the virtual roads of the exotic landscape using the car metaphor. The customizable road network based visualization is promising as it presents an overview and detailed information all in one place. This is augmented by a simple and easy to use interface, and multi-modal interactions for better navigation. The road network uses real world traffic symbols and a mapping paradigms so that the learners feel comfortable to find information of interest. In effect, searching for information is replaced by the discovery of destinations with guided road directions.

In our prototype the information that is to be mapped over the road network, following specific protocols (discussed in later section) are search results that consist of LOM records [1]. The prototype includes different optional components that, as a whole, function like search interface. We have employed a novel organization and presentation technique where topics of interest can be retrieved from any information repository [14]. Overall, the techniques effectively illustrates relations, creates identifiable patterns and reduces the information overload to facilitate learners or teachers effectiveness in navigating, exploring, and searching information.

2.1. Related study

WWW3D [17] is a 3D browser integrating the display of web pages, browsing environment and navigation history. In addition, it supports concurrent users who are visible to each other. The metaphor lacks realism in its information representation. Moreover, understanding the relationships within the documents are difficult and the user interface lacks intuitiveness in its control. Cellary [7] presents a Periscope visualization model to visualize web search result in 3D. In this scheme, each glyph represents a single document, and the user can assign different attributes to glyph including levels. Here, the levels correspond to servers hosting documents which is intuitive for browsing information but it fails to show the actual context and relationship within the document level. Also the document presented with different colors lacks detailed information from which it could be identified. The Mediametro prototype [9], presents a visualization scheme of multimedia document collections using 3D city metaphor. The document thumbnails are depicted over the buildings from which it is easy to discriminate their type information. Virtual helicopter-based landscape navigation had been introduced to perceive the media information. Such a navigation scheme and selection tactics are tedious and may require practice to become accustomed. Also, the experience could be enhanced by presenting a game-like user avatar model to entertain the learner. We have presented a 3D gaming metaphor for visualizing search results in a virtual environment and gaming is one of the most effective ways of teaching about complex scenarios - and keeps the users engaged.

2.2. The partition model

The metaphor presents graphical controls where the learner can enter the keywords to be searched. Figure 1 describes the information flow in the process. The keyword to be searched, is sent to the thesaurus look up module to obtain more relevant keywords (eg. for keyword 'language' we would get speech, spoken language, terminology, lyric, word). The extraction of the thesaurus is inspired by current psycholinguistic theories of human lexical memory [3]. We are using hypernym semantic relations to find out the link in the synonym sets.

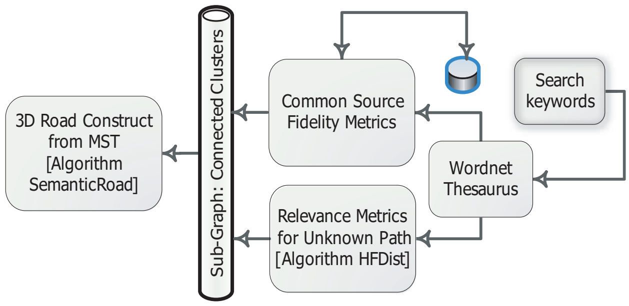

Figure 1. Architecture illustrating the 3D road network construction model from semantic information

After obtaining all the relevant keywords, the search is initiated (to appropriate search repository). The search results are analyzed in order to obtain new keywords and ranks are calculated for all the keywords. We have described the portion of the adopted ranking method in one of our previous works [16]. These ranked keywords are then taken further into consideration to discover the common source fidelity metrics. Whenever some unknown relationship is encountered in the previous process it is sent to the relevance metrics calculation module. The relevance metrics exploration is governed by a number of postulates, as we will find in the subsequent sections. As soon as the processing is complete, the results are lead to a threaded pipeline where they are acted upon to determine the visual representation of the semantic distances.

3. Semantics of Keywords

WordNet [3] is a semantic lexicon which groups English words into sets of synonyms and records the semantic relations among the synonym sets. Using the relationship models (eg. hypernym) we have introduced a search result clustering scheme. Whenever the user enters one or more keywords in the search query interface, we compute a bag of words with distance between the parsed keywords. The search results are inherently grouped and ranked by relevance based on this distance metrics. We describe the distance measurement scheme used in our experiment, inspired by the model proposed in [11]. To begin with, clustering of the search results requires a grouping scheme, which depends on a number of components:

- Number of keywords found in the search results
- Keywords frequency in the search results
- Hypernym distance between the keywords
- Hypernym relation between the keywords

However it is unlikely that the hypernym distances of the keywords would always be found. Therefore the hypernym relation detection algorithm has to be modified to consider special cases.

3.1. Keyword relationship metrics

In this section we will discuss and define our postulates in order to find metrics that could be used to cluster the search results. Initial inquiry suggests that ranking ($\Re$) of the keywords is related to the frequency (Γ) of the keywords found in the search results, which is shown in equation 1:

$$\Re(\kappa) \approx \Gamma(\kappa) \tag{1}$$

Using the WordNet lexical thesaurus database we can determine and calculate hypernym relation metrics between keyword κ and keyword g using the following equation,

$$\Im(\kappa, g) \cong \sqrt{\left|\hbar_\partial(g)^2 - \bar{M}^2\right|} \tag{2}$$

Where, $0 < g < length(K)$ and K is the set of keywords for a given search results, $\hbar_\partial(g)$ denotes the direct hypernym distance from κ to g in the lexical database, and $\bar{M}$ is the average of the calculated hypernym distances from κ to all other keywords in K. Whenever possible a direct hypernym relation between the search keywords should be calculated using the equation 2. However, if there is no direct hypernym distance of $\hbar_\partial(g)$ that exists for the keyword pair $< \kappa, g >$ then a third keyword could be used to establish the relationship.

$$\Im(\kappa, g) \cong \sqrt{\left|\underbrace{\min\{\hbar_\partial(\kappa, \ell) + \hbar_\partial(\ell, g)\}^2}_{\ell \,\exists\, K} - 2\bar{M}^2\right|} \tag{3}$$

Again, in order to apply the equation 3, two parameters needed to be present in the keyword matrix. A hypernym relation between κ to ℓ and another is between ℓ to g. For trivial cases, let us consider that no such keywords exists for which both of the parameters could be deduced. For example, we calculated the hypernym distance $\hbar_\partial(\kappa, \ell)$ but were unable to process $\hbar_\partial(\ell, g)$ in the above equation. In this case we can apply the following postulates to assign a reasonably less correct value and apply the clustering in the 3D environment.

In order to calculate $\Im(\kappa, g)$ we will choose a certain value of $\hbar_\partial(\ell, g) \approx \epsilon$, which maximizes the assigned value of the equation.

$$\Im(\kappa, g) \cong \sqrt{\left|\underbrace{\{\hbar_\partial(\kappa, \ell) + \epsilon\}^2}_{\lambda_{\min} < \epsilon < \lambda_{\max}} - 2\bar{M}^2\right|} \tag{4}$$

In equation 4, $\lambda_{\min}\, and\, \lambda_{\max}$ are the minimum and maximum values respectively returned by the $\hbar_\partial(\kappa, g)$ in the entire calculation of the hypernym distance set for the keywords. Finally, the ranking of the distances that would be used to calculate the clustering of the keywords in the virtual environment could be found by the following equation,

$$H(\kappa) \cong \sum_{0<g<length(K)} \Im(\kappa, g)/\Re(\kappa) \tag{5}$$

In equation 5, the lower value of $H(\kappa, g)$ means the higher ranking of the keyword κ with respect to the keyword g. Hence, considering these three cases, the algorithm for the ad-hoc hypernym distance calculation could be summarized as follows:

Algorithm HFDistance (*Vector searchResult*)
$Begin$

/ The algorithm takes the vector (in this case XML formatted search records) search result and applies the hypernym distance calculation to find out semantics between the keywords */*

1. Find out all the distinct keywords from the search results and add them to the keyword set K

2. Calculate the frequency for each keyword in K and update the frequency list as in equation 1

3. Add all the combinations of keyword pairs in the data structure $< \kappa_i, \kappa_j, flag = 0 >$ in the Queue Q_κ along with a flag value to determine the cycle of procession of the pairs

4. While $(\tau \leftarrow dequeue(Q_\kappa))\, not\, null$ do the following

   i. Remove the element τ from the Q_κ

   ii. If $flag = 0$ then process the keyword pair and try to apply equation 2 to calculate the hypernym distance between the keywords. If successful then record the result and continue the loop, else increment the flag value of τ and $enqueue(Q_\kappa)$ return

   iii. If $flag = 1$ then apply heuristic to find a keyword in K that relates the pair τ using equation 3. Therefore, if the keyword ℓ is found that satisfies the equation then record the result and continue loop else increment the flag value of τ and $enqueue(Q_\kappa)$ return

   iv. */* the algorithm asserts that there exists at least one relationship in the keyword sets for which the hypernym relationship could be calculated by using equation 2, otherwise the algorithm can not produce hypernym distance matrix and the necessary relationship metrics */*
   Apply equation 4 to calculate the hypernym distance and record the result

   v. If a complete cycle does not yield any changes in the elements of the Q_κ, exit the loop

End Algorithm HFDistance

For example, with a particular keyword 'language' and its thesaurus, the application of the above algorithm provides us with the following results listed in the matrix 2. As could be seen 'language' is related with all of its synonyms except 'speech'. There are no direct hypernym relation that exists between these two, therefore the algorithm has to apply and deduce a less correct value to reflect their poor relationship.

The algorithm effectively uses the common parent index and the relevance metrics calculating procedure to deduce the relationship matrix. Table 1 lists the summation of all the relationships between these keywords. The table provides very important guidance to the visualization engine. This is because it reflects the root keyword to which other

Hypernym semantics	
Keywords set	**CPI summation**
language	13.485
speech	35.675
spoken language	14
terminology	23.1
lyric	29.03
words	18.87

Table 1. Asymmetric hypernym semantics for keyword: language

$$\begin{pmatrix} 0 & 7.485 & 1 & 3 & 1 & 1 \\ 7.48 & 0 & 6.79 & 7.125 & 6.96 & 7.32 \\ 2 & 6 & 0 & 4 & 2 & 0 \\ 4 & 7.1 & 4 & 0 & 4 & 4 \\ 5 & 7.03 & 5 & 7 & 0 & 5 \\ 3 & 6.87 & 1 & 5 & 3 & 0 \end{pmatrix}$$

Table 2. The graph consists of the hypernym semantic distances for the set of keywords

keywords are related with the least paths (therefore they are very related).

This is essentially the reason why the least valued keyword is considered as the root (starting node) in the final constructed road network. In the visualization procedure the root is the group that will be mapped in the first road in the metaphor as it contains the most relevant information sought by the learner. The semantics of keywords as described above are the correct indications that the algorithm works in a way to justify the process. Therefore the output that we get from the algorithm has the possibility to be used in the visualization scheme.

3.2. Construction of the Road Network

After calculating the matrix values for the keyword sets, the next major step is to use the metrics in clustering the groups in the virtual environment. In order to determine the clustering and the degree of the group nodes, we have applied the minimum spanning tree (MST) [10] over the matrix. Therefore, the resultant spanning tree consists of the edges from individual keyword nodes that are of the minimum semantic distances. Minimum spanning trees are proven to be useful in our case as for the following reasons

- The computation time is quick and simple and

- The algorithm results a sparse subgraph that reflects a lot about the original graph. This is suitable with our approach,
- There are no cycles in the final subgraph, therefore, this results in the possibility of designing a road network very easily (as described in the following algorithm)

The resultant subgraph is further sent to the visualization engine where the semantic distances are converted to a visual representation (in this case, road network) to establish meaning and pattern. The algorithm SemanticRoad is such a visualization approach.

Algorithm SemanticRoad (*Vector searchResult*)
$Begin$

/ The algorithm takes the vector graph containing the semantics of the keywords in matrix form (calculated hypernym distances). MST is applied to get the subgraph which is then processed considering various customizable parameters to form the road network where the search result could be mapped easily. */*

1. Extract the graph information and apply the MST
   / After we have a subgraph where all the nodes are connected and no cycles exist in the graph*/*
   For *each* node υ of the subgraph *do* the following
2. if ($Taken(\upsilon) == false$) then
   / The node is the root of the whole road structure */*
   i. Mark the node as taken
   ii. Calculate the color value for the group to distinguish itself from others,
   $\upsilon(C) = Color(\upsilon)$ */* Each keyword is unique in the keyword set*/*
   iii. Therefore, the minimum length of the road ς could be determined as following
   $\upsilon(\varsigma) = \max\{degree(\upsilon) * \eta, count(\upsilon) * \delta\}$
   where η = minimum distance between two parallel branch roads and δ = minimum distance between two traffic signs containing LOM records.
   / Hence, the size of any road is chosen considering the number of partitions of the road (node degree) into parallel roads and fitting all the search results related to this keyword inside it*/*
   iv. Assign predefined 3D positions for the root road
   v. Calculate position values for each nodes that are connected with υ and toggle the direction of the branch roads so that one road directs on the left and the next one on the right, thereby effectively positioning the roads to use available space over the virtual environment. Finally, mark all the connected roads as taken.
3. else */* The node is a child node and its position has already been calculated */*
   Repeat steps ii and iii of the above in order to calculate the distinct color value and road length of this node and then apply step *v* to determine the position values for each of the connected nodes with $Taken(\upsilon) == false$

End Algorithm SemanticRoad

It should be noted, though very unlikely, the roads comprising greater semantic distances may cross each other. Therefore, a unique color value is chosen from the keyword (as keywords are unique) and is applied to respective roads to separate them. This is essentially the reason that we toggle the directions of the side roads while connecting them with the parent road. Moreover, using MST instead of pure graph is one of the tactics we employed to avoid the cross between roads in the final road network. The road size calculation is another important issue. The number of side roads (to connect relevant search groups) that appear from a parent road depends on the degree of the node as well as the number of search items in the parent group. Therefore, the trade off is to take the maximum size that would accommodate all the search items and connect all the side roads to the parent road keeping moderate distances between them.

4. Implementation and result study

The highway metaphor was implemented using OpenGL [2]. The metaphor comprises of a game like virtual environment, as indicated by figure 2, and it presents a number of important features. It has an interface for searching LOMs. In addition a customizable search repository (either local or remote), a speech recognition based command, audio synthesis based feedback, a world overview layout for efficient navigation and a real world traffic system based guidance system (directing the learner to his information of interest) makes the learning experience entertaining and intuitive.

The run time of the algorithm (HFDistance) and the semantic road construction algorithm depends mainly on the selection of keywords. For a particular keyword the number of relevant keywords may vary and would create different run time behavior. Figure 3 depicts the run time of the algorithm in terms of keywords. As observed while testing the method the upper boundary for the run time of the algorithm is $O(n^2)$. In most cases as the number of keywords are few (average 10–20) therefore the metrics calculation method is feasible enough for a real time application.

It is interesting to note the construction behavior of the algorithm SemanticRoad. The worst-case scenario occurs when the semantic distances produced by the HFDist method are too similar. In this case, it would only partition

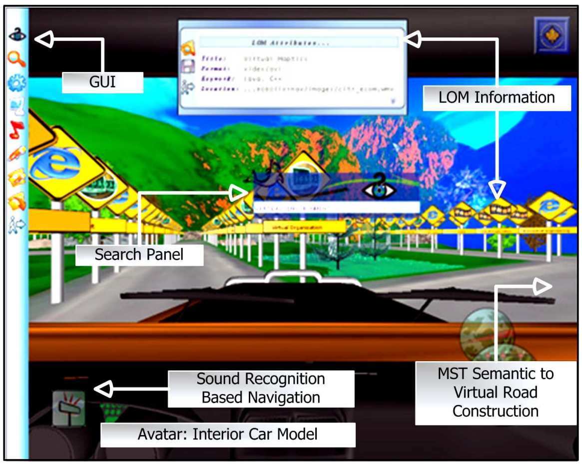

Figure 2. The game like highway metaphor, exploiting LOM group relationship

the first root node with others as its side roads and (with the trade off in road size calculation) its search result would be distributed along a very long length thereby degrading the navigation process. The best-case scenario would be where each of the roads have only one partition (degree one) therefore, each road would allow only one passage to its relevant search group enhancing the information clustering process.

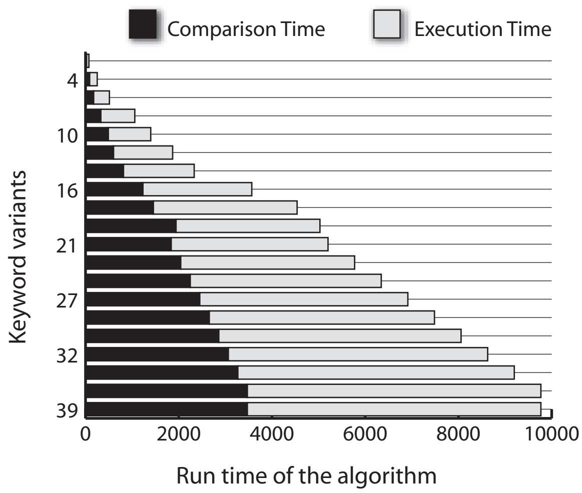

Figure 3. The run time behavior study of the Algorithm SemanticRoad

5. Conclusions

We have discussed the importance of appropriate information visualization tools to convey meaningful sight of the 'big picture'. This is followed by a brief discussion of the major roles of visual metaphors in exploiting information to the learners. A game motivated 3D highway metaphor has been presented where novel partitioning and clustering techniques for the search results have been introduced. An algorithm has been presented to describe the semantic metrics calculation method. Along with mathematical illustrations of the process, we have presented a way of using the metrics by converting those to their respective visual representations. The 3D highway metaphor displays these interactive constructs, presents relationships visually that exist among the set of information and provides an intuitive and entertaining way of searching, browsing, and navigating information.

In our future studies, we want to undergo extensive usability testing of the metaphor, which would allow us to find out the acceptance of the 3D prototype. Based on the same semantic metrics presented in this paper, a light weight-internet browser compatible metaphor (preferably in different scenario) would be a nice implementation. Finally, a peer to peer collaborative metaphor model could be proposed where the learners will be able to search, and share information.

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