AN OPTIMIZED REVIEW OF ADAPTIVE HYPERMEDIA AND WEB PERSONALIZATION – SHARING THE SAME OBJECTIVE

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Abstract: A traditional system presents the same static explanation and suggests the same next page to all users, even though they might have widely differing knowledge of the subject. Such a system suffers from an inability to be all things to all people, especially when the user population is relatively diverse; users often lose sight of the goal of their inquiry, look for stimulating rather than informative material, or even use the navigational features unwisely. To this end, researchers and practitioners studied adaptivity and personalization to address the comprehension and orientation difficulties presented in such systems to alleviate such navigational difficulties and instead, satisfy the heterogeneous needs of the user population. This paper investigates the relationship between these two areas of research which effectively share the same goal: to adapt according to the specific user characteristics.

1 INTRODUCTION

There is a growing body of empirical evidence to suggest that users tend to make poor decisions in traditional systems as the navigational freedom given to the user leads to comprehension and orientation difficulties in the sense that users may become spatially disoriented, lose sight of objectives, skip important content, choose not to answer questions, look for stimulating rather than informative material or simply use the navigational features unwisely. Since the user population is relatively diverse, such traditional static applications suffer from an inability to satisfy the heterogeneous needs of the many users. Adaptivity is a particular functionality that alleviates navigational difficulties by distinguishing between interactions of different users within the information space. Adaptive Systems employ adaptivity by manipulating the link structure or by altering the presentation of information, based on a basis of a dynamic understanding of the individual user, represented in an explicit user model.

To this end, researchers and practitioners studied adaptivity and personalization to address the comprehension and orientation difficulties presented in such systems to alleviate such navigational difficulties and instead, satisfy the heterogeneous needs of the user population. Adaptive Hypermedia and Web Personalization are two distinct research fields that share the same goal: to adapt according to the specific user requirements.

Adaptive Hypermedia is a relatively old and well established area of research counting three generations: The first "pre-Web" generation of adaptive hypermedia systems explored mainly adaptive presentation and adaptive navigation support and concentrated on modeling user knowledge and goals. The second "Web" generation extended the scope of adaptive hypermedia by exploring adaptive content selection and adaptive recommendation based on modeling user interests. The third "New Adaptive Web" generation moves adaptive hypermedia beyond traditional borders of desktop hypermedia systems embracing such modern Web trends as "mobile Web", "open Web", and "Semantic Web" [Brusilovsky, 2003]. On the other hand, Web Personalization refers to the whole process of collecting, classifying and analyzing Web data, and determining based on these the actions that should be performed so that the user is presented with personalized information. As inferred from its name, Web Personalization refers to Web applications solely, and generally is a relatively new area of research.

This paper investigates the relationship between these two areas of research which effectively share the same goal. Section 2 presents an overview of Adaptive Hypermedia techniques. Section 3 makes a reference to Web Personalization, and section 4 describes the Web Personalization paradigms. Section 5 presents a comparison between the two research fields, and section 6 concludes this paper.

2 ADAPTIVE HYPERMEDIA OVERVIEW

Adaptivity is a particular functionality that alleviates navigational difficulties by distinguishing between interactions of different users within the information space [Eklund and Sinclair, 2000; Brusilovsky and Nejdl, 2004]. Adaptive Hypermedia Systems employ adaptivity by manipulating the link structure or by altering the presentation of information, based on a basis of a dynamic understanding of the individual user, represented in an explicit user model [Eklund and Sinclair, 2000; De Bra *et al*., 1999; Brusilovsky, 2001; Brusilovsky, 1996a; Brusilovsky, 1996b].

In the 1997 discussion forum on Adaptive Hypertext and Hypermedia, an agreed definition of adaptive hypermedia systems was reached after Brusilovsky [Eklund and Sinclair, 2000] as follows: "By Adaptive Hypermedia Systems we mean all hypertext and hypermedia systems which reflect some features of the user in the user model and apply this model to adapt various visible and functional aspects of the system to the user." [Eklund and Sinclair, 2000; Brusilovsky, 1996b]

A system can be classified as an Adaptive Hypermedia System if it is based on hypermedia, has an explicit user-model representing certain characteristics of the user, has a domain model which is a set of relationships between knowledge elements in the information space, and is capable of modifying some visible or functional part of the system based on the information maintained in the user-model [Eklund and Sinclair, 2000; Brusilovsky and Nejdl, 2004; Brusilovsky, 1996b].

In 1996, Brusilovsky identified four user characteristics to which an Adaptive Hypermedia System should adapt [Brusilovsky, 1996b; Brusilovsky, 2001]. These were user's knowledge, goals, background and hypertext experience, and user's preferences. In 2001, further two sources of adaptation were added to this list, user's interests and individual traits, while a third source of different nature having to deal with the user's environment had also been identified.

Generally, Adaptive Hypermedia Systems can be useful in application areas where the hyperspace is reasonably large and the user population is relatively diverse in terms of the above user characteristics [Brusilovsky, 2001; Brusilovsky, 1996a; Brusilovsky and Nejdl, 2004; Brusilovsky, 1996b]. A review by Brusilovsky has identified six specific application areas for adaptive hypermedia systems since 1996 [Brusilovsky, 2001]. These are educational hypermedia, on-line information systems, information retrieval systems, institutional hypermedia and systems for managing personalized view in information spaces. Educational hypermedia and on-line information systems are the most popular, accounting for about two thirds of the research efforts in adaptive hypermedia.

Adaptation effects vary from one system to another. These effects are grouped into three major adaptation technologies - adaptive content selection [Brusilovsky and Nejdl, 2004], adaptive presentation (or content-level adaptation) and adaptive navigation support (or link-level adaptation) [Eklund and Sinclair, 2000; De Bra *et al*., 1999; Brusilovsky, 2001; Brusilovsky and Peylo, 2003; Brusilovsky, 1999; Brusilovsky, 1996a; Brusilovsky, 1996b; Brusilovsky and Nejdl, 2004; Brusilovsky, 2003; Bailey *et al*., 2002; Brusilovsky and Pesin, 1998; Bulterman *et al.*, 1999] and are summarized in Figure 1. Adaptive Hypermedia Techniques.

The first of these three technologies comes from the field of adaptive information retrieval (IR) and is associated with a search-based access to information. When the user searches for relevant information, the system can adaptively select and prioritize the most relevant items [Brusilovsky and Nejdl, 2004].

The idea of adaptive presentation is to adapt the content of a page to the characteristics of the user according to the user model [Eklund and Sinclair, 2000; De Bra *et al*., 1999; Brusilovsky, 2001; Brusilovsky and Pesin, 1998]. With such techniques the content is individually generated or assembled from pieces for each user, to contain additional information, pre-requisite information or comparative explanations by conditionally showing, hiding, highlighting or dimming fragments on a page [De Bra *et al*., 1999]. The granularity may vary from word replacement to the substitution of pages to the application of different media. Adaptive presentation techniques have been classified into: (a) adaptive multimedia presentation, (b) adaptive text presentation, and (c) adaptation of modality [Brusilovsky and Nejdl, 2004; Brusilovsky and Pesin, 1998].

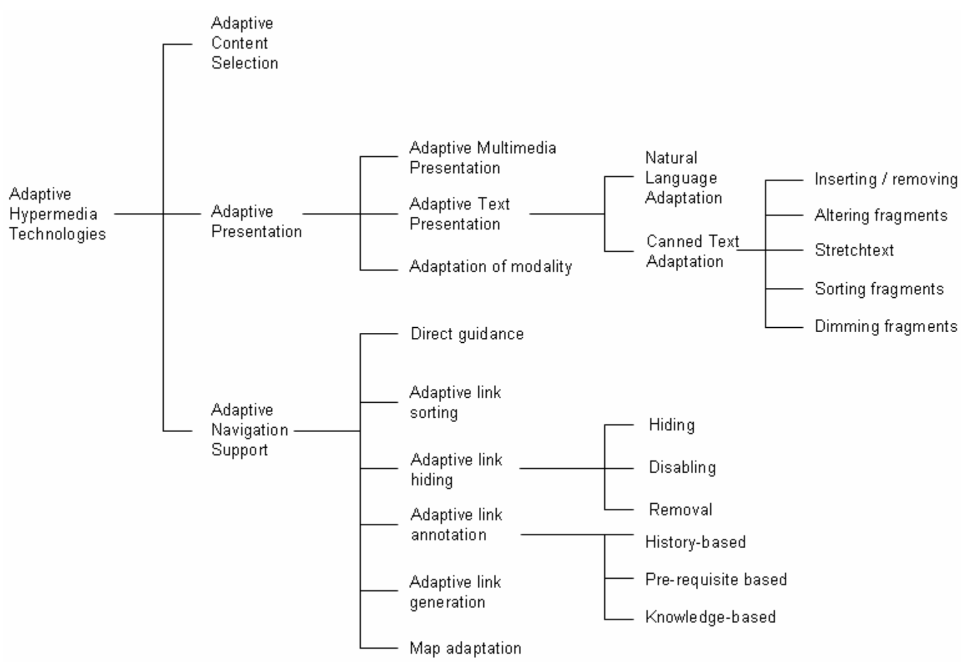

Figure 1. Adaptive Hypermedia Techniques

Adaptive navigation techniques have been classified according to the way they adapt the presentation of links, ranging from methods that restrict the user's interactions with the content to techniques that aid the user in their understanding of the information space, aiming provide either orientation or guidance [Eklund and Sinclair, 2000]. Orientation informs the user about their place in the hyperspace while guidance is related to a user's goal. These techniques are: direct guidance [Eklund and Sinclair, 2000; Brusilovsky and Pesin, 1998]; adaptive link sorting [Eklund and Sinclair, 2000; Brusilovsky and Pesin, 1998]; adaptive link hiding [Eklund and Sinclair, 2000; Brusilovsky and Pesin, 1998]; adaptive link annotation [Brusilovsky and Pesin, 1998]; adaptive link generation [Brusilovsky, 2001; Brusilovsky and Nejdl, 2004]; and map adaptation [Brusilovsky, 1996b].

3 WEB PERSONALIZATION OVERVIEW

Web personalization is the process of customizing the content and structure of a Web site to the specific needs of each user by taking advantage of the user's navigational behaviour. Being a multi-dimensional and complicated area a universal definition has not been agreed to date. Nevertheless, most of the definitions given to personalization [Cingil *et al.*, 2000; Blom, 2000; Kim, 2002; Wang and Lin, 2002] agree that the steps of the Web personalization process include: (1) the collection of Web data, (2) the modelling and categorization of these data (pre-processing phase), (3) the analysis of the collected data, and the determination of the actions that should be performed. Moreover, many argue that emotional or mental needs, caused by external influences, should also be taken into account.

Personalization could be realized in one of two ways: (a) Web sites that require users to register and provide information about their interests, and (b) Web sites that only require the registration of users so that they can be identified [De Bra *et al.*, 2004]. The main motivation points for personalization can be divided into those that are primarily to facilitate the work and those that are primarily to accommodate social requirements. The former motivational subcategory contains the categories of enabling access to information content, accommodating work goals, and accommodating individual differences, while the latter eliciting an emotional response and expressing identity [Wang and Lin, 2002].

Personalization levels have been classified into: Link Personalization, Content Personalization, Context Personalization, Authorized Personalization and Humanized Personalization.

Link Personalization involves selecting the links that are more relevant to the user, changing the original navigation space by reducing or improving the relationships between nodes. E-commerce applications use link personalization to recommend items based on the clients' buying history or some categorization of clients based on ratings and opinions. Link personalization is widely used in Amazon.com to link the home page with recommendations, new releases, shopping groups, etc. [Rossi *et al.*, 2001]

When content becomes personalized, user interface can present different information for different users providing substantive information in a node, other than link anchors. Most of the content personalization research is relative to text and hypertext personalization and can be further classified into two types:

(a) Node structure customization (personalization) usually appears in those sites that filter the information that is relevant for the user, showing only sections and details in which the user may be interested. The user may explicitly indicate their preferences, or these may be inferred (semi-) automatically either from the user profile or navigation activity. For example, in my.yahoo.com or in www.mycnn.com users choose a set of "modules" and further personalize those modules by choosing a set of attributes of the module to be perceived. Some "automatic" customization may occur based on location information (e.g. by using the zip code of the user to select local to the user sport events). The outcome of these applications is that the user should be able to "build" their own page.

(b) Node content customization (personalization) occurs when different users perceive different values for the same node attribute; this kind of content personalization is finer grained than structure personalization. A good example can be found in online stores that give customers special discounts according to their buying history (in this case the attribute price of item is personalized) [Rossi et al., 2001].

Personalizing navigational contexts is critical when the same information (node) can be reached in different situations [Rossi *et al.*, 2001]. A navigational context is a set of nodes that usually share some property. For example in a Conference Paper Review Application, it is possible to access papers etc. Notice that one paper may appear in different sets and that different users may have different access restrictions according to their role in the Review application. Context personalization can also be adapted to the preferences of the learner and semantics of the learner's current environment. One sub-category of context personalization is terminal adaptivity. That is adapting information to the characteristics of a device. It is applied on the mobile devices to satisfy learner's demand for "learning as you go". Terminal Personalization occurs on a per session basis. Personalization can be achieved by applying many axes of adaptation effecting both the navigational structure and appearance of the learning experience. It involves the tailoring of a resource to the current environment of the learner [Lankhorst *et al.*, 2002].

With Authorized Personalization, different users have different roles and therefore they might have different access authorizations. For example, in an academic application, instructors and students have different tasks to perform. Instructors want to access their class materials, such as upload, edit their class syllabus and give students' grades etc. On the other hand, students want to access the interface to find out their current GPA, their enrolment status, and their course work status etc.

Humanized Personalization involves human computer interaction. If this dimension of the "emotional user interface" could be involved, it will be a huge step towards a concrete and universal definition of Web personalization. Unquestionably, this category of personalization still needs to be explored, with an extensive use of Artificial Intelligence technologies [Kaplan *et al*., 1999]. Kaplan *et al.* [1999] made a first step towards exploring this area when they implemented an intelligent interactive telephone system (Telephone-Linked Care (TLC)) that provided information whether they were talking to a machine or to a person during TKC relationships with the TLC system [Hjelsvold *et al*., 2001].

4 WEB PERSONALIZATION TECHNOLOGIES

4.1 Content-Based Filtering

Systems that are implementing these kinds of techniques are solely based on individual users' preferences. The system tracks each user's behavior and recommends items that are similar to items the user liked in the past. It is based on description analysis of the items rated by the user and correlations between the content of these items and user's preferences. It is an alternative paradigm that has been used mainly in the context of recommending items such as books, Web pages, news, etc. for which informative content descriptors exist [Pazzani, 2005, Basilico and Hofmann, 2004; Shardanand and Maes, 1995]. This technique is primarily characterized by two weaknesses, content Limitations and over-Specialization. There are content limitations like IR methods that can only be applied to a few kinds of content, such as text and image, and the extent aspects can only capture certain aspects of the content. On the other hand content-based recommendation systems provide recommendations merely based on user profiles, therefore, users have no chance of exploring new items that are not similar to those items included in their profiles and thus leading to over-specialization. Consequently, some more drawbacks that have been identified in time are [Shahabi and Chen, 2003; Shardanand and Maes, 1995; Mobasher *et al*., 2002]:

(a) Search-based models build keyword, category, and author indexes offline, but fail to provide recommendations with interesting, targeted titles. They also scale poorly for customers with numerous purchases and ratings.
(b) User input may be subjective and prone to bias.
(c) Explicit (and non-binary) user ratings may not be available.
(d) Profiles may be static and can become outdated quickly.
(e) May miss other semantic relationships among objects.

At this point it would be noteworthy to mention a complementary technique of Content-based filtering, namely Social Information filtering. It essentially automates the process "word-of-mouth" recommendations: items are recommended to a user based upon values assigned by other people with similar taste. The system determines which users have similar taste via standard formulas for computing statistical correlations. Social Information filtering overcomes some of the limitations of content-based filtering. Items being filtered need not be amenable to parsing by a computer. Furthermore, the system may recommend items to the user which are very different (content-wise) from what the user has indicated liking before. Finally, recommendations are based on the quality of items, rather than more objective properties of the items themselves [Shardanand and Maes, 1995; Mobasher *et al*., 2002]. Some of the most popular systems using content-based filtering are WebWatcher, and client-side agent Letizia [Chaffee and Gauch, 2000].

4.2 Rule-Based Filtering

The users are asked to answer a set of questions. These questions are derived from a decision tree, so as the user proceeds to answer them. What he finally receives is a result (e.g. list of products) tailored to his needs. Content-based, rule-based, and collaborative filtering may also be used in combination, for deducing more accurate conclusions. Some of the rule-based filtering drawbacks are: User input may be subjective and prone to bias, explicit (and non-binary) user ratings may not be available, profiles may be static and can become outdated quickly, and for large systems it becomes burdensome to manage. Related interesting systems include Dell, Apple Computer, Amazon.com, CDNOW, and Broadvision [Mobasher *et al*., 2002; Shardanand and Maes, 1995; Wang and Lin, 2002; Eirinaki and Vazirgiannis, 2003].

4.3 Collaborative Filtering

Systems invite users to rate the objects or divulge their preferences and interests and then return information that is predicted to be of interest to them. This is based on the assumption that users with similar behavior (e.g. users that are rate similar objects) have analogous interests. There are two general classes of collaborative filtering algorithms, memory-based methods and model-based methods [Wang and Lin, 2002; Eirinaki and Vazirgiannis, 2003, Pazzani, 2005; Basilico and Hofmann, 2004]. Moreover, the goals in a collaborative filtering system are basically focused upon the reduction of computation time, the increase of the extent in which predictions can be computed in parallel, and the increase of prediction accuracy. Collaborative filtering can further refine the process of giving each individual personal recommendation compared to rule-based filtering. It overcomes the drawbacks of the content-based filtering because it typically does not use the actual content of the items for recommendation. It usually works based on assumptions. With this algorithm the similarity between the users is evaluated based on their ratings of products, and the recommendation is generated considering the items visited by nearest neighbors of the user. In its original form, the nearest-neighbor algorithm uses a two-dimensional user-item matrix to represent the user profiles. This original form suffers from three problems, scalability, sparsity, and synonymy [Shahabi and Chen, 2003; Papagelis *et al*., 2004]. Some more highlighted drawbacks of collaborative filtering are focused upon: (a) Collaborative-filtering techniques are often based in matching in real-time the current user's profile against similar records obtained by the systems over time from other users. However, as noted in recent studies, it becomes hard to scale collaborative filtering techniques to a large number of items, while maintaining reasonable prediction performance and accuracy. Part of this is due to the increasing sparsity in the data as the number of items increase. One potential solution to this problem is to first cluster user records with similar characteristics, and focus the search for nearest neighbors only in the matching clusters. In the context of Web personalization this task involves clustering user transactions identified in the preprocessing stage; (b) traditional collaborative filtering does little or no offline computation, and its online computation scales with the number of customers and catalog items. The algorithm is impractical on large data sets, unless it uses dimensionality reduction, sampling, or partitioning – all of which reduce recommendation quality; (c) user input may be subjective and prone to bias; (d) explicit (and non-binary) user ratings may not be available; (e) profiles may be static and can become outdated quickly; (f) they are not able to recommend new items that have not already been rated by other users. An object will become available for recommendation only when many users have seen it and rated it, making it part of their profiles first ("latency problem"); (g) they are not satisfactory when dealing with a user that is not similar enough with any of the existing users [Mobasher *et al*., 2002; Mobasher *et al*., 2000; Vozalis et al., 2001]. Some systems applied with this technique are Yahoo, Excite, Microsoft Network, Net Perceptions [Eirinaki and Vazirgiannis, 2003].

4.4 Web Usage Mining

The typical sub-categorization of the Web mining research field falls into the following three categories: Web-content mining, Web-structure mining, and Web usage mining. The prerequisite step to all of the techniques for providing users with recommendations is the identification of a set of user sessions from the raw usage data provided by the Web server. Web usage mining is the only category related to Web Personalization. This process relies on the application of statistical and data mining methods to the Web log data, resulting in a set of useful patterns that indicate users' navigational behavior. The data mining methods that are employed are: Association rule-mining, sequential pattern discovery, clustering, and classification. Given the site map structure and usage logs, a Web usage miner provides results regarding usage patterns, user behavior, session and user clusters, click stream information, and so on. Additional information about the individual users can be obtained by the user profiles [Deshpande and Karypis, 2004; Eirinaki and Vazirgiannis, 2003; Cingil *et al.*, 2000]. The overall process can be divided into two components. (a) The offline component is comprised of the pre-processing and data preparation tasks, including data cleaning, filtering, and transaction identification, resulting in a user transaction file, and (b) the data mining stage in which usage patterns are discovered via specific usage mining techniques such as association-rule mining, association-rule discovery and usage clustering [Mobasher *et al*., 2000]. The increasing focus on Web-usage mining as the time passes derives from some key characteristics which are summarized as follows: (a) the profiles are dynamically obtained, from user patterns, and thus the system performance does not degrade over time as the profiles age; (b) using content similarly alone as a way to obtain aggregate profiles may result in missing important relationships among Web objects based on their usage. Thus, Web usage mining will reduce the need for obtaining subjective user ratings or registration-based personal preferences; (c) profiles are based on objective information (how users actually use the site); (d) there is no explicit user ratings or interaction with users (saves time and other complications); (e) it helps preserve user privacy, by making effective use of anonymous data; (f) the usage data captures relationships missed by content-based approaches; (g) it can help enhance the effectiveness of collaborative or content-based filtering techniques. Nevertheless, usage-based personalization can be problematic when little usage data is available pertaining to some objects or when the site content attributes of a site must be integrated into a Web mining framework and used by the recommendation engine in a uniform manner [Mobasher *et al*., 2002]. Noteworthy applications are Alta-Vista, Lycos, WebSift, and SpeedTracer [Pierrakos *et al.*, 2001; Eirinaki and Vazirgiannis, 2003].

4.5 Demographic-Based Filtering

This specific technique could be roughly described as an approach that uses demographic information to identify the types of users that prefers a certain object and to identify one of the several pre-existing clusters to which a user belongs and to tailor recommendations based on information about others in this cluster [Pazzani, 2005; Basilico and Hofmann, 2004].

4.6 Agent Technologies

Agents are processes with the aim of performing tasks for their users, usually with autonomy, playing the role of personal assistants [Delicato *et al.* 2001; Panayiotou and Samaras, 2004]. Agents usually solve common problems users experience on the Web such as personal history, shortcuts, page watching and traffic lights. Some of the agents' main characteristics could be distinguished according to their abilities used and according to the tasks they execute. The former include characteristics such as *intelligence*, *autonomy*, *social capacity* (inter-agent communication), and *mobility*; while the latter classify the agents into *information filtering agents*, *information retrieval agents*, *recommendation agents*, *agents for electronic market*, and *agents for network management* [Delicato *et al.* 2001]. Pioneer personalization systems implemented with agents are: ARCHIMIDES, Proteus, WBI, BASAR, 1:1 Pro, Haystack, eRACE, mPersona, Fenix system, and SmartClient [Pu and Faltings, 2002; Panayiotou and Samaras, 2004; Delicato *et al.* 2001;]

4.7 Cluster Models

These types of techniques are found mostly in the area of eCommerce and could be characterized as eCommerce recommendation algorithms. To find customers who are similar to the user, cluster models divide the customer base into many segments and treat the task as a classification problem. The algorithm's goal is to assign the user to the segment containing the most similar customers. It then uses the purchases and ratings of the customers in the segment to generate recommendations. The segments typically are created using a clustering or other unsupervised learning algorithm, although some applications use manually determined segments. Using a similarity metric, a clustering algorithm groups the most similar customers together to form clusters or segments. Because optimal clustering over large data sets is impractical, most applications use various forms of greedy cluster generation. These algorithms typically start with an initial set of segments, which often contain one randomly selected customer each. They then repeatedly match customers to the existing segments, usually with some provision for creating new or merging existing segments. For very large data sets – especially those with high dimensionality – sampling or dimensionality reduction is also necessary. Once the algorithm generates the segments, it computes the user's similarity to vectors that summarize each segment, chooses the segment with the strongest similarity and classifies the user accordingly. Some algorithms classify users into multiple segments and describe the strength of each relationship [Perkowitz and Etzioni, 2003]. Cluster models have better online scalability and performance than collaborative filtering because they compare the user to a controlled number of segments rather than the entire customer base. The complex and expensive clustering computation is run offline. However, recommendation quality is relatively poor. To improve it, it is possible to increase the number of segments, but this makes the online user segment classification expensive. Typical examples of eCommerce systems are Amazon.com [Rossi *et al.*, 2001], Dell [Eirinaki and Vazirgiannis, 2003], and IBM.com [Karat *et al.*, 2003].

5 SIMILARITIES AND DIFFERENCES

After having seen a brief overview of what Adaptive Hypermedia and Web Personalization is all about it is only a matter of time to spot out their similarities and differences. The most evident similarity is the objective of these two research fields: to develop techniques to adapt what is presented to the user, based on the specific user needs.

Generally, Adaptive Hypermedia refers to the manipulation of the link or content structure of an application to achieve adaptation and makes use of an explicit user model [Eklund and Sinclair, 2000; De Bra et al., 1999; Brusilovsky, 2001; Brusilovsky, 1996a; Brusilovsky, 1996b]. Adaptive Hypermedia is a relatively old and well established area of research counting three generations: The first "pre-Web" generation of adaptive hypermedia systems explored mainly adaptive presentation and adaptive navigation support and concentrated on modeling user knowledge and goals. The second "Web" generation extended the scope of adaptive hypermedia by exploring adaptive content selection and adaptive recommendation based on modeling user interests. The third “New Adaptive Web” generation moves adaptive hypermedia beyond traditional borders of desktop hypermedia systems embracing such modern Web trends as “mobile Web”, “open Web”, and “Semantic Web” [Brusilovsky, 2003]. On the other hand, Web Personalization refers to the whole process of collecting, classifying and analyzing Web data, and determining based on these the actions that should be performed so that the user is presented with personalized information. As inferred from its name, Web Personalization refers to Web applications solely, and is a relatively new area of research.

One could also argue that the areas of application of these two research areas are different, as Adaptive Hypermedia has found popular use in educational hypermedia and on-line information systems [Brusilovsky, 2001], where as Web Personalization has found popular use in eBusiness services delivery. From this, it could be inferred that Web Personalization has a more extended scope that Adaptive Hypermedia, exploring adaptive content selection and adaptive recommendation based on modeling user interests.

Also, the reason for the need of such areas to be researched is the quite similar.

The most evident technical similarity is that they both make use of a user model to achieve their goal. However, the way they maintain the user profile is different; Adaptive Hypermedia requires a continuous interaction with the user, while Web Personalization employs algorithms that continuously follow the users’ navigational behavior without any explicit interaction with the user.

Technically, two of the adaptation / personalization techniques used are the same. These are adaptive-navigation support (of Adaptive Hypermedia and else referred to as link-level adaptation) and Link Personalization (of Web Personalization) and adaptive presentation (of Adaptive Hypermedia and else referred to as content-level adaptation) and Content Personalization (of Web Personalization).

Last but not least, it is noteworthy to mention that both research fields make use of Artificial Intelligence techniques.

6 CONCLUSION

Adaptive Hypermedia and Web Personalization are two distinct well established areas of research both investigating methods and techniques to move conventional static systems beyond traditional borders to more intelligent, adaptive and personalized implementations, a common goal: to alleviate navigational difficulties and satisfy the heterogeneous needs of the user population by adapting according to user specific characteristics.

Adaptive Hypermedia is older than Web Personalization counting three generations: The first "pre-Web" generation of adaptive hypermedia systems explored mainly adaptive presentation and adaptive navigation support and concentrated on modeling user knowledge and goals. The second "Web" generation extended the scope of adaptive hypermedia by exploring adaptive content selection and adaptive recommendation based on modeling user interests. The third “New Adaptive Web” generation moves adaptive hypermedia beyond traditional borders of desktop hypermedia systems embracing such modern Web trends as “mobile Web”, “open Web”, and “Semantic Web” [Brusilovsky, 2003]. On the other hand, and as inferred from its name, Web Personalization refers to Web applications solely, and describes the whole process from the collection, classification and analysis of Web data, to the determination based on these the actions that should be performed so that the user is presented with personalized information.

REFERENCES

[Eklund and Sinclair, 2000] Eklund J. and Sinclair K. *An empirical appraisal of the effectiveness of adaptive interfaces of instructional systems*. Educational Technology and Society 3 (4), ISSN 1436-4522, 2000.

[Brusilovsky and Nejdl, 2004] Brusilovsky P. and Nejdl W. *Adaptive Hypermedia and Adaptive Web*, © 2004 CSC Press LLC.

[De Bra *et al*., 1999] De Bra P., Brusilovsky P., and Houben G. *Adaptive Hypermedia: From systems to framework*, ACM Computing Surveys 31(4), 1999

[Brusilovsky, 2001] Brusilovsky P. *Adaptive Hypermedia*, User Modeling and User-Adapted Interaction 11: 87-110., 2001

[Brusilovsky, 1996a] Brusilovsky P. *Adaptive Hypermedia: an attempt to analyse and generalize*, In P. Brusilovsky, P. Kommers, & Streitz (Eds.), Multimedia, Hypermedia, and Virtual Reality, Berlin: Springer-Verlag, 288-304., 1996

[Brusilovsky, 1996b] Brusilovsky P. *Methods and techniques of adaptive hypermedia*, User Modeling and User Adapted Interaction, 1996, v6, n 2-3, pp 87-129., 1996

[Brusilovsky and Peylo, 2003] Brusilovsky P.,& Peylo C. *Adaptive and Intelligent Web-based Educational Systems*, International Journal of Artificial Intelligence in Education 13 (2003) 156-169., 2003

[Brusilovsky, 1999] Brusilovsky, P. *Adaptive and Intelligent Technologies for Web-based Education*. In C. Rollinger and C. Peylo (eds.), Special Issue on Intelligent Systems and Teleteaching, *Künstliche Intelligenz*, 4, 19-25., 1999

[Brusilovsky, 2003] Brusilovsky P. *From Adaptive Hypermedia to the Adaptive Web*, G.Szwillus, J.Ziegler (Hrsg): Mensch & Computer 2003: Interaktion in Bewegung, Stuttgart: B. G. Teubner, 2003, S. 21-24., 2003

[Bailey *et al*., 2002] Bailey C., Hall W., Millard D., & Weal M. *Towards Open Adaptive Hypermedia*, In Proceedings of the Second International Conference on Adaptive Hypermedia and Adaptive Web Based Systems, Malaga, Spain, LNCS 2347, Springer, pp. 36-46., 2002

[Brusilovsky and Pesin, 1998] Brusilovsky, P. and Pesin, L. *Adaptive navigation support in educational hypermedia: An evaluation of the ISIS-Tutor*, Journal of Computing and Information Technology 6 (1), 27-38., 1998

[Bulterman *et al.*, 1999] Bulterman D.C.A., Rutledge L., Hardman L., & Ossenbruggen J. *Supporting adaptive and adaptable hypermedia presentantion semantics*, Database Semantics 8 Submission., 1999

[Cingil *et al.*, 2000] Cingil I., Dogac A., & Azgin A. A broader approach to personalization, Communications of the ACM, Vol. 43, No. 8., 2000

[Blom, 2000] Blom J. Personalization – A Taxonomy, ACM 2000. ISBN:1-58113-248-4., 2000

[Kim, 2002] Kim W. Personalization: Definition, Status, and Challenges Ahead, Published by ETH Zurich, Chair of Software Engineering JOT, ©2002, Vol. 1, No. 1., 2002

[Wang and Lin, 2002] Wang J., & Lin J. Are personalization systems really personal? – Effects of conformity in reducing information overload, Proceedings of the 36th Hawaii International Conference on Systems Sciences (HICSS'03), 0-7695-1874-5/03, © 2002 IEEE., 2002

[De Bra *et al*., 2004] De Bra P., Aroyo L., & Chepegin V. *The next big thing: Adaptive Web-based systems*, Journal of Digital Information, Vol. 5 Issue 1, Article no. 247., 2004

[Rossi *et al*., 2001] Rossi G., Schwade D., & Guimaraes M.R. *Designing Personalized Web Applications*, ACM 1-58113-348-0/01/0005., 2001

[Lankhorst *et al*., 2002] Lankhorst M.M., Kranenburg, Salden A., & Peddemors A.J.H. *Enabling Technology for Personalizing Mobile Services*, Proceedings of the 35th Annual Hawaii International Conference on System Sciences (HICSS-35'02)., 2002

[Kaplan *et al*., 1999] Kaplan, B., Farzanfar, R. and Friedman R.H. *Research and Ethical Issues Arising from Ethnographic Interviews of Patients' Reactions to an Intelligent Interactive Telephone Health Behavior Advisor System*, in: Ngwenyama, O., Introna, L.D., Myers, M.D. and DeGross, J.I. (Eds) New Information Technologies in Organizational Processes: Field Studies and Theoretical Reflections on the Future of Work, Boston: Kluwer Academic Publishers, 67-77., 1999

[Hjelsvold *et al*., 2001]Hjelsvold R., Vdaygiri S., & Leaute Y. *Web –based personalization and management of interactive video*, ACM 1-58113-348-0/01/0005., 2001

[Pazzani, 2005] Pazzani J. M. *A framework for collaborative, content-based and demographic filtering.* Artificial Intelligence Review, December 1999, vol. 13, no. 5-6, pp. 393-408(16), 2005

[Basilico and Hofmann, 2004] Basilico J., & Hofmann T. *Unifying collaborative and content-based filtering*, Proceedings of the 21st International Conference on Machine Learning, Banff, Canada., 2004

[Shardanand and Maes, 1995] Shardanand U. and Maes, *Social information filtering: Algorithms for automating "Word of Mouth"*, Proceedings of CHI'95 -- Human Factors in Computing Systems, 210-217, 1995

[Shahabi and Chen, 2003] Shahabi C. and Chen Y., *Web Information Personalization: Challenges and Approaches*, at the 3nd International Workshop on Databases in Networked Information Systems (DNIS 2003), Aizu-Wakamatsu, Japan, 2003

[Mobasher *et al*., 2002] Mobasher B., DaiH., Luo T.,Nakagawa M., & Wiltshire J. *Discovery of aggregate usage profiles for Web personalization*, Data Mining and Knowledge Discovery, Volume 6, Issue 1, pp. 61 – 82, 2002

[Chaffee and Gauch, 2000] Chaffee J., & Gauch S. Personal Ontologies for Web Navigation, ACM 2000, 1-58113-320-0/00/11., 2000

[Eirinaki and Vazirgiannis, 2003] Eirinaki M., & Vazirgiannis M. Web Mining for Web Personalization, ACM Transactions on Internet Technology, Vol. 3, No. 1, Pages 1-27., 2003

[Papagelis *et al*., 2004] Papagelis M., Plexousakis D., Rousidis D., & Theoharopoulos E. *Qualitative Analysis of User-based and Item-based Prediction Algorithms for Recommendation Systems*, CIA 2004: 152-166., 2004

[Mobasher *et al*., 2000] Mobasher B., Colley R., and Strivastava J., Communications of the ACM, Volume 43, Issue 8, 0001-0782, pp. 142 – 151, 2000

[Vozalis et al., 2001] Vozalis E., Nicolaou A., & Margaritis K. G. Intelligent Techniques for Web Applications: Review and Educational Application, presented at the Fifth Hellenic-European Conference on Computer Mathematics and its Applications (HERCMA), Athens, Greece., 2001

[Deshpande and Karypis, 2004] Deshpande M., & Karypis G. *Selective Markov models for predicting Web page accesses*, ACM Transactions on Internet Technologies, Vol. 4, No. 2, Pages 163-184., 2004

[Pierrakos *et al.*, 2001] Pierrakos D., Paliouras G., Papatheodorou C., Spyropoulos C.D., *KOINOTITES: A Web Usage Mining Tool for Personalization*, Proceedings of the Panhellenic Conference on Human Computer Interaction, Patra, 2001

[Delicato *et al.*, 2001] Delicato F., Pirmez L., & Carmo L., *Fenix – personalized information filtering system for WWW pages*, Internet Research: Electronic Networking Applications and Policy, Vol. 11, No. 1, pp. 42-48, 2001

[Panayiotou and Samaras, 2004] Panayiotou C., & Samaras G., *mPersona: Personalized Portals for the Wireless User: An Agent Approach*, Journal of ACM/ Baltzer Mobile Networking and Applications (MONET), special issue on "Mobile and Pervasive Commerce", 2004

[Perkowitz and Etzioni, 2003] Perkowitz M, & Etzioni O., *Adaptive Websites*, Towards Adaptive Web sites: Conceptual Framework and case study, [online], http://www.cse.buffalo.edu/~sbraynov/seninar2003/presenttations/adaptive.pdf, 2003

[Rossi *et al.*, 2001] Rossi G., Schwade D., & Guimaraes M.R., *Designing Personalized Web Applications*, ACM 1-58113-348-0/01/0005, 2001

[Eirinaki and Vazirgiannis, 2003] Eirinaki M., & Vazirgiannis M., *Web Mining for Web Personalization*, ACM Transactions on Internet Technology, Vol. 3, No. 1, Pages 1-27, 2003

[Karat *et al.*, 2003] Karat M.C., Brodie C., Karat J., Vergo J., & Alpert S.R., *Personalizing the user experience on ibm.com*, IBM Systems Journal, Vol. 42, No. 4, 2003

[Pu and Faltings, 2002] Pu P., & Faltings B., *Personalized Navigation of Heterogeneous Products Spaces using SmartClient*, © 2002 ACM 1-58113-459-2/02/0001/, 2002