Personalization of web based interactive systems using computational intelligence techniques

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ABSTRACT

The research presented in this paper focuses on personalization of WBIS using computational intelligence (CI) methods. The scope of this research is first given and then developments in each aspect are explained. Taxonomy for personalization of WBIS using eight identified CI techniques is presented. Comparison of these eight CI techniques is made and reasons given for selection of a neuro-swarm hybrid CI model for investigation of personalization. A created MATLAB add-in for implementation of this neuro-swarm model is then used to show superior performance of PSO over backpropagation for NN training. A model for personalization of eLearning systems by neuro-swarm determination of learning style is presented. Results of a simulation for the personalization of the structure of a course in Moodle, using the neuro-swarm model, are then given.

Author Keywords

Personalization, Computational Intelligence, Web based interactive systems, user modeling.

INTRODUCTION

The Internet grew from 2000 to 2010 at an estimated rate of 445% [1]. With this accelerated growth rate the size and complexity of many websites grow along with it. Millions of users continually face great difficulty interacting with web interfaces as they are bombarded with a world of information at each click. This is commonly known as the information overload problem.

Web personalization is a major part of user-centered design which addresses this research problem and has been defined as any set of actions that can tailor the Web experience to a particular user or a set of users [1]. Personalization techniques for WBIS seek to better learn about users of the system so that accurate user models can be created for satisfying users' needs and preferences. Analysis of mined web usage data has proven to be a valuable source of hidden information on user needs and preferences [6]. There is a direct relationship between the accuracy of user preferences determined from mined usage data and effective interface personalization.

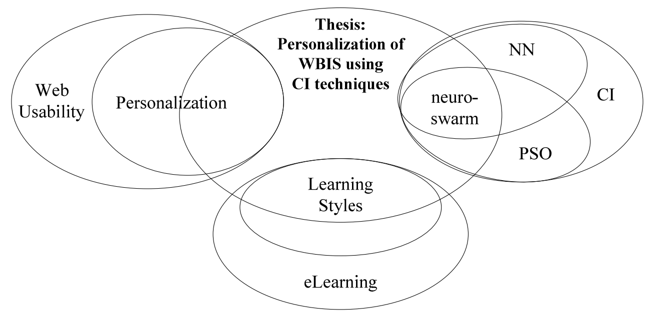

Figure 4: Scope of research.

Techniques which can accurately determine user needs and preferences, for user modeling, from mined web usage data are therefore important for personalization. Some traditional techniques which use mined usage data to address this information overload problem include information filtering, information extraction, information retrieval and collaborative filtering. Common problems in gathering, processing and analyzing web usage data using these traditional techniques are scalability, processing time and accuracy of learning. To help overcome these shortcomings of traditional methods, techniques which artificially mimic the intelligence of users have been investigated such as Computational Intelligence (CI) methods. CI techniques keep memory about user needs and preferences and are so able to dynamically adjust to changing user patterns and make personalized recommendations [6, 8]. An extensive review of literature for CI models regarding their fit to personalize WBIS found that there was a lack of systematic review and taxonomy in this area.

The aim of this research therefore, is to improve the ability of personalized WBIS to satisfy users' needs and preferences by using CI techniques for more accurate user modeling. illustrates the scope of this research. From it can be seen that personalization of WBIS is a subcategory of Web Usability. This is combined with a hybrid CI technique, neuro-swarm, which is a combination of Neural Networks (NN) and Particle Swarm Optimization (PSO) techniques. This neuro-swarm technique is applied

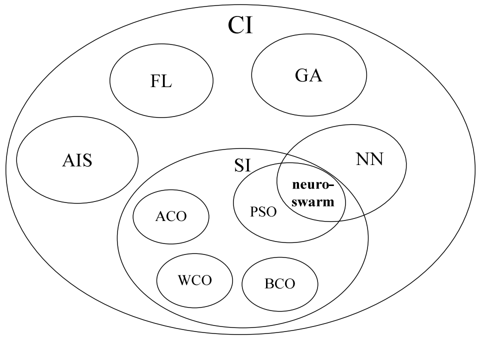

Figure 5: Computational Intelligence models.

for personalization eLearning by focusing on learning style determination.

In the following sections the CI techniques considered within this research scope are identified. Next taxonomy for personalization of WBIS using these identified CI techniques is given. Based in this taxonomy comparison of the models are made which results in the selection of a neuro-swarm model for further investigation. The next section introduces a neuro-swarm model for determining learning styles of students. Afterwards, results of one simulation of this model for a course on Moodle are given. The last section presents conclusions and future work.

COMPUTATIONAL INTELLIGENCE MODELS FOR PERSONALIZATION OF WEB BASED INTERACTIVE SYSTEMS

CI has been defined as "the study of adaptive mechanisms to enable or facilitate intelligent behavior in complex and changing environments" [3]. This is an ongoing and evolving area of research since its term was coined by John McCarthy in 1956. For this research, CI models identified were Neural Networks (NN), Artificial Immune Systems (AIS), Genetic Algorithms (GA) which is a major subcategory of Evolutionary Algorithms (EA), Fuzzy Logic (FL) which is a major subcategory of Fuzzy Systems (FS) and four subcategories of Swarm Intelligence (SI) which are Ant Colony Optimization (ACO), Wasp Colony Optimization (WCO), Bee Colony Optimization (BCO) and Particle Swarm Optimization (PSO). These techniques were critically reviewed regarding their application to personalization of web-based systems. Various applications of each of these techniques were found in literature, however there was found no comparison of the techniques and recommendations for use.

The authors previously filled this gap in research by presenting a taxonomy for the personalization of web based systems [5]. Based on an extensive literature review of these CI techniques, in [5] we classified these CI models for personalization of WBIS as illustrated in Figure 6. As shown in Figure 6, this taxonomy proposes two main personalization categories as profile generation and profile exploitation. For profile generation FL, NN, PSO, GA, ACO and AIS were found to be the main CI techniques used and also a hybrid between GA and NN. For profile exploitation CI applications were found using FL, GA and BCO for navigation and FL, GA, WCO, NN and PSO for content personalization. Hybrid methods were also identified.

To show how this taxonomy fits into the overall personalization procedure for a WBIS, Figure 7 illustrates the main steps in the personalization process, outlining the flow of information and distinguishing between profile generation processes and profile exploitation processes.

Based on this taxonomy, Figure 8, comparisons were made based on five criteria which are simplicity of the method, speed of convergence, how sound or wholesome is its theoretical background, the model's ability to learn and adapt to given input and how much research has been done on testing the model. In Figure 8, ☺ indicates that the model was found to perform well in comparison to the other models and ☹ indicates that model did not perform well in comparison to the others.

Research studies show that PSO outperforms GA [6] and ACO [7]. PSO has relatively few parameters as compared to NN and has a more sound theoretical foundation than AIS. PSO is also relatively easier to program and easier to interpret than FL. Of the five methods presented for profile generation using WUM data, PSO seems to be the more tested, useful and well rounded method.

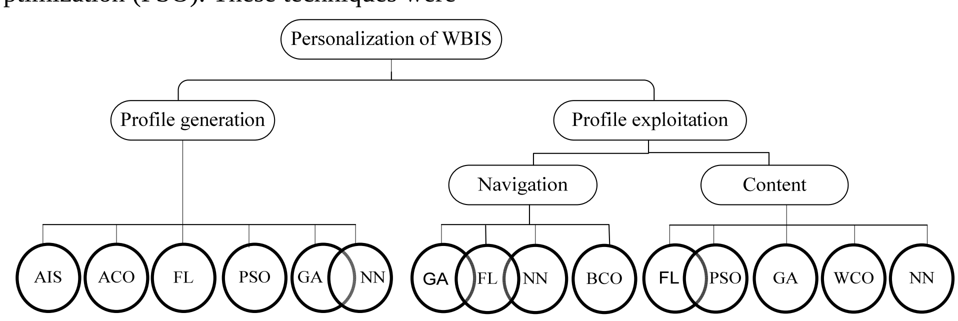

Figure 6: Taxonomy for personalization of web-based systems by CI models.

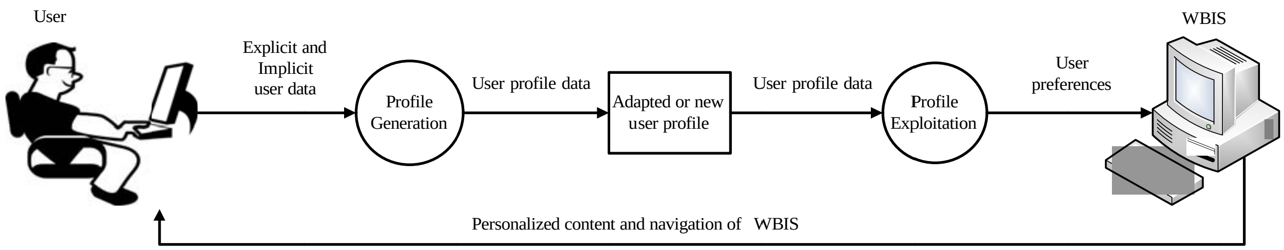

Figure 7: Procedure for personalization of interactive web systems based on taxonomy.

In hybrid techniques it was found that the strength of one method complemented the weakness of another. PSO was credited with good performance as compared to the other methods however, it is not without its flaws. From this taxonomy and the comparison that followed, it was decided that a neuro-swarm model is a worthy candidate for investigation for personalization of WBIS.

This neuro-swarm model is a NN that is trained by PSO. In literature, PSO for NN training was found to succeed in overcoming inefficiencies of the most common NN training algorithms known as back propagation training algorithms [2]. Updated predefined tools for PSO training of NNs was not found to exist in MATLAB, the chosen program for implementations of this research. A MATLAB add-in was therefore developed that interfaces MATLAB's NN toolbox and a predefined PSO toolbox [4]. This add-in was tested and worked for MATLAB versions 2008 and newer. This add-in has been uploaded to the Mathworks website and is now freely available to the public for download [10]. At the time this paper was written, there has been more than one hundred downloads of this add-in.

Simulations were done to validate the superiority of PSO for NN training using the created add-in in MATLAB. Figure 9 and Figure 10 show the result of training a NN by two different training algorithms but the same training data and other NN settings given in Figure 13 and Figure 14. The figures show that the backpropagation NN training, Figure 9, took 2000 epochs to minimize the NN training error to 0.023. However PSO NN training, Figure 10, took 647 epochs to minimize the error to 0.0009. From these results, among many similar simulation results, the superiority of PSO for NN training over backpropagation, and using the created add-in is evident.

A NEURO-SWARM MODEL FOR PERSONALIZATION IN ELEARNING

Considering students' learning styles in online courses and providing personalization based on students' learning styles has high potential to make learning easier for students. Therefore, creating an accurate student model, which includes the students' learning styles, is important for personalization of one type of WBIS, eLearning systems. In this section a neuro-swarm model is presented which determines students' learning styles based on the Felder Silverman Learning Style Model (FSLSM) [1], using data from students' behavior gathered while students are learning in an online course.

Several techniques exist to determine learning styles. One approach for automatic student modeling of learning styles is to use a rule-based mechanism [4] however, this approach while simple, fails to take into account vital

	CI Models								Hybrids			
	FL	GA	NN	PSO	ACO	BCO	WCO	AIS	FL-PSO	FL-NN	FL-GA	GA-NN
Simplicity	☹		☹	☺								
Speed	☺	☹	☹	☺	☹				☺			☺
Sound theory	☺			☺	☺	☹	☹	☹				
Learning ability				☺					☺	☺	☺	☺
Well tested	☺	☺		☺		☹	☹	☹		☹		☹

Figure 8: Comparisons of CI models for personalization.

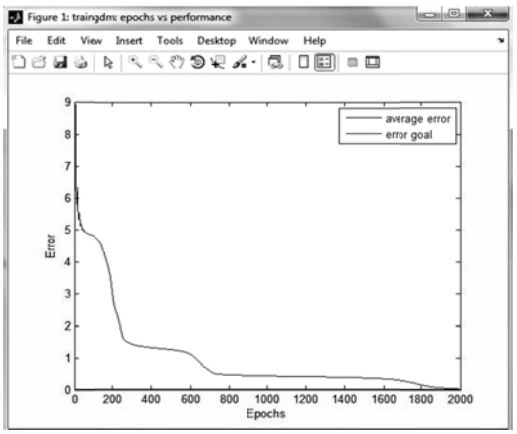

Figure 9: Result of NN training by a backpropagation method.

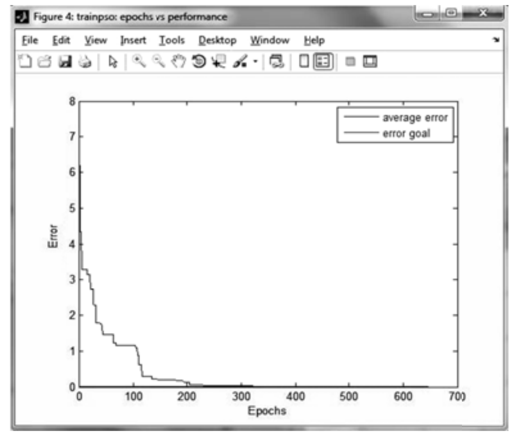

Figure 10: Result of NN training by a PSO method.

factors such as different weightings of input, dependencies among inputs and possible useful historical data. Intelligent approaches to learning style determination have also previously been investigated such as Bayesian Networks [1]. BNs take into account weights and interdependencies of variables which the rule based approach fails to do. Shortcoming of Bayesian Networks however are difficulties in determining probability values used and in examination of the solutions of BNs, computationally complex to implement, time consuming to perform and there can exists some software limitations. Fuzzy cognitive map is another intelligent technique used to determine students learning style [2] and uses fuzzy logic methods to determine learning style by the Kolb's learning style model. Some disadvantages of this fuzzy cognitive method is inherent in the shortcoming of fuzzy logic itself which include , it is not discrete, maybe hard to follow, does not always give a definitive answer, and can be difficult to program. To overcome the shortcomings of existing ways to determine learning styles, this paper presents a neuro-swarm optimization model for learning style.

NN structure

Figure 11 illustrates the basic structure of the NNs to determine students' learning style for student modeling.

For each of the four learning style dimensions of the FSLSM, one NN is created. Therefore, four NNs are associated with each course as shown. Each NN has an input layer, a hidden layer and an output layer. Furthermore, in literature two layered FNN were found to provide good results for non linear approximations []. The number of nodes in the hidden layer is a matter of trial and error but for this implementation half the number of input nodes was found to give acceptable results.

NN inputs

The input values for all the NNs are implicitly monitored students' behavior as students interact with the LMS as was studied in [4]. From that study, each dimension of the FSLSM was found to have associated online student behavior patterns, which here are the respective NN inputs

NN output

Each NN has one output which is in the range 0 to 1. Each value in this range indicates a particular strength of each learning style as shown in the example given with the active/reflective learning style dimension in Figure 12.

NN targets

Target values for training these NNs are calculated based on questionnaire results, gathered from students at the beginning of the course,

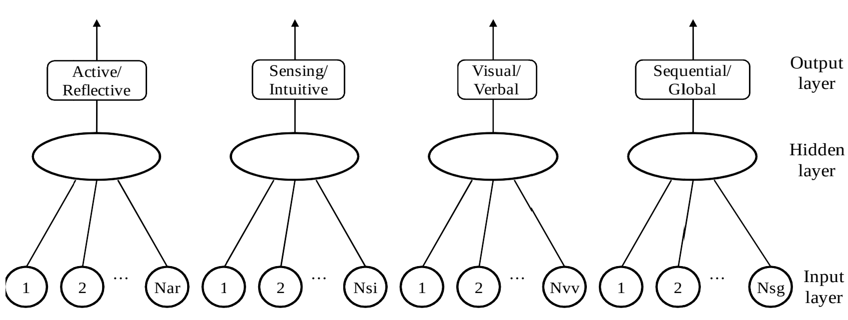

Figure 11: NNs for determination of learning style.

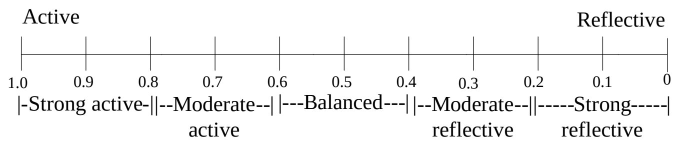

Figure 12: Output range of Neural Networks used to determine learning style.

which give an explicit indication of their learning preferences.

NN training

For NN weights and biases initialization and optimization, PSO is used as previously explained. NN and PSO settings for implementation of the neuro-swarm model are shown in the MATLAB workspace screenshots, Figure 13and Figure 14.

SIMULATION RESULTS

Simulations have been made to demonstrate the implementation and use of NNs to determine students' learning style in a real life project involving the Web Usability course. Assuming four NNs have been created and trained as briefly explained in the previous section, here is illustrated the personalized Moodle interface based on the results from a simulation of the neuro-swarm model. Figure 15 illustrates the exact NN structure for the Visual/Verbal learning style dimension in one such simulation.

Using simulated students' behavior patterns and passing the behavior of one student to the four trained NNs the resulting NN outputs indicating the student's LS were 0.92 for Active/Reflective, 0.90 for Sensing/intuitive, 0.65 for Visual/verbal and 0.75 for Sequential/global.

These learning style values indicate that the student has a strong active, strong sensing, average sequential and moderate visual learning style [5]. Based on the study done in [5] the structure of the eLearning interface, Moodle in this implementation, is adapted accordingly.

Figure 16 and Figure 17 show comparisons of the Moodle interface for a simulation without and with personalization

```
Neural Network (NN) settings:
NN training function:traingdm
NN layers:2
NN training goal:0.001
NN maximum epochs:2000
NN maximum time:Inf
```

Figure 13: Screenshot of MATLAB workspace showing the settings for all NNs used in this simulation.

```
PSO settings:
Global Best (gbest) PSO
2000 iterations maximum
Position clamping active.
Velocities clamped to 50% of the range on each dimension.
1 trial(s)
25 particles
Inertia weight linearly varied from 0.9 to 0.4 per grouping.
Cognitive acceleration coefficient, c1: 1.49618
Social acceleration coefficient,    c2: 1.49618
NN: 66 dimensions
Symmetric Initialization: [-1,1]
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Figure 14: Screenshot of MATLAB workspace showing the PSO settings used in this simulation.

based on the neuro-swarm learning style results given previously.

CONCLUSION AND FUTURE WORK

In this paper is presented an overview of research done on personalization of WBIS using computational intelligence techniques. The scope of this research interest incorporates work in the areas of personalization, computational intelligence and with application in eLearning. Eight CI techniques were identified and taxonomy for personalization of WBIS was presented which categorises these eight CI techniques into two profile generation and profile exploitation. These CI techniques were further analysed and compared which resulted in the selection of a neuro-swarm model for further research for personalization

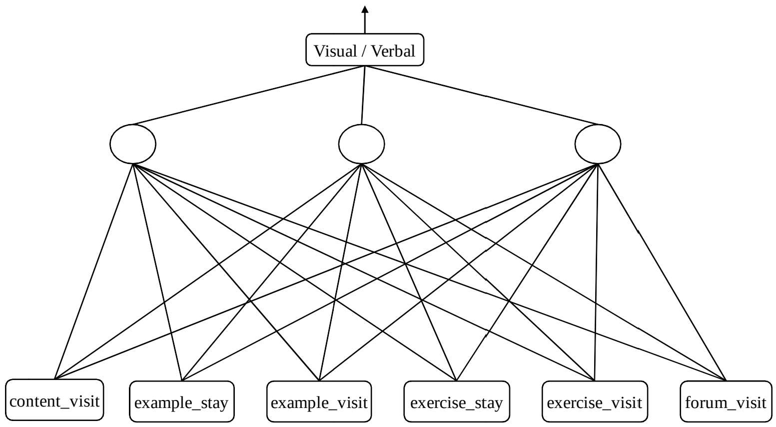

Figure 15: NN structure for the Visual/Verbal learning style dimension.

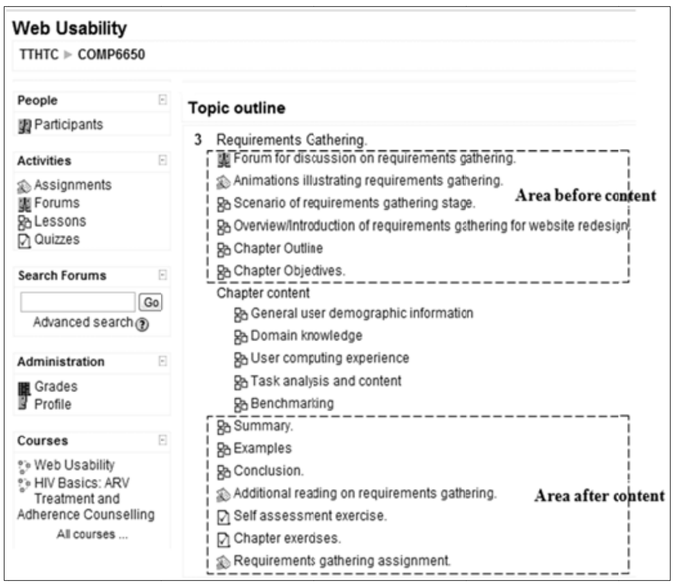

Figure 16: Moodle interface without personalization.

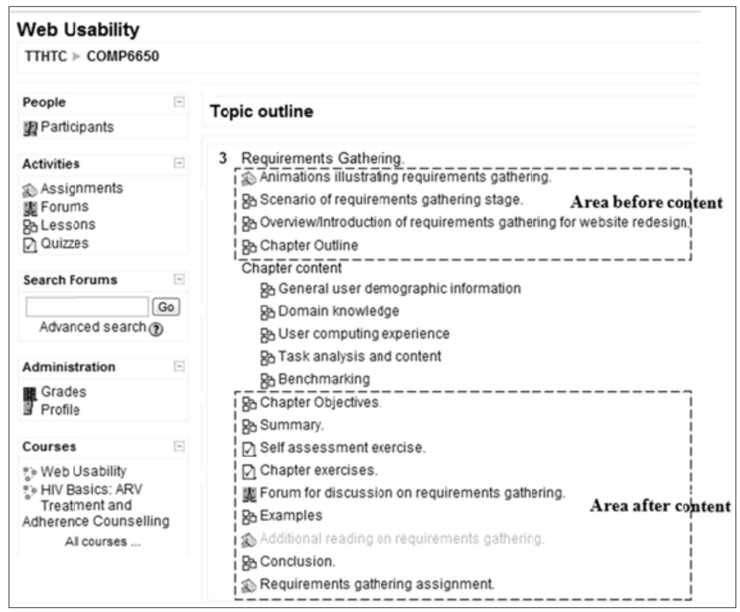

Figure 17: Adapted Moodle interface for a student with a strong active, strong sensing, average sequential and moderate visual learning style.

A model for personalization in eLearning, using the selected neuro-swarm model, was then explained and implemented with simulation results given.

Future work involves real life implementation of the neuro-swarm model for automatic personalization of a course on Moodle and also providing personalized recommendations to students based on this model. Validation of the accuracy and effective of this approach to personalization will be done by comparing the results of the neuro-swarm model to Rule Based and Bayesian networks approach, for learning style determination using real data, and also usability testing of the personalized interface.

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