Automatic Profile Generation for Visual-Impaired Users

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Abstract. Currently, there are a growing number of tools that allow web developers to evaluate the accessibility of their web pages and sites. Many tools also prompt the developer to make specific repairs; and some tools automatically follow links to evaluate multiple pages within a site or within an entire domain. Although tools such as these can be very useful to identify accessibility problems, many accessibility issues are subjective and cannot be assessed without manual inspection. We believe that accessibility assessment and repair should be addressed as related activities intelligently supported. To do so, a main aspect to be considered is the automatic identification of user disabilities. In this paper we introduce an agent-based solution to tackle this problem. The agent is conceived to provide knowledge for the creation and classification of visually-impaired users profiles in terms of stereotypes. We apply and test the performance of our agent by profiling surveyed users. Our solution will be part of a multi-agent system to drive intelligently the accessibility conformance process.

Keywords: User Profile, Intelligent Agent, Visual Disabilities

1 Introduction

The importance of automatically identifying users can be significant given a wide variety of applications on the Web, such as products for electronic commerce, e-government, social networks, etc. Information and organization are determined by the needs of users, whether they are actual or potential, without excluding those with limitations - disabilities, language skills or limitations with respect to access context, software and hardware, connection bandwidth, etc.[1]. Particularly, Web accessibility refers to the inclusive practice of making websites usable by people of all abilities and disabilities. To do so, many efforts take as references the Web Content Accessibility Guidelines 1.0 [3] and 2.0 [4].

Currently, there are some efforts towards automating Web accessibility aspects. For instance, inspection may be automated by using systems capable of analyzing and recommending, such as TAW [5], Bobby [2], and WAVE [6]. These systems aim at evaluating strengths and weaknesses of Web sites focusing on allowing designers to improve Web accessibility. As another case, it is also possible to automatically evaluate formats of web documents, for example by using GAEL [7] taking advantage of its reasoning capabilities.

When addressing automatic repairing, supporting tools should rather be intelligent in that they adapt themselves to the individual constraints and current situation of people to provide a service most likely in the line with the user's intentions and goals. Techniques, based on concepts of artificial intelligence, are desirable as tools of repair and transformation, due to the need to simplifying the decision-making process, and reducing human intervention. However, the limited existence of intelligence in current tools ([7–11]), makes a user to decide about the operation process.

Most of the existing evaluation and repair tools adhere to current Web accessibility standards and support different formats of Web documents. However, there is a gap between the existing support and the real needs in terms of intelligent and automatic detection of Web accessibility barriers. This fact made us to focus on solving such barriers, to identify users by applying smart features. To do so, we have selected an agent-based solution, where the goal of the agent is to provide information and expertise on a specific topic: the creation and classification of users' profiles in terms of stereotypes, considering visual limitations that a user owns.

This paper is organized as follows. The next section presents our model for classifying visual-impaired users by means of stereotypes. Then, the automatic profile generation is introduced through the agent-based solution, and a motivating case study illustrates the proposal. Conclusion and future work is addressed afterwards.

2 Visual-Impaired User Profile Modeling

When creating accessible Web applications, our first concern is about centering the process in "all users". During this process, the more we know the users, the closer we are to their needs and therefore, the more usable and accessible the application may be. User modeling consists of defining user profiles taking common attributes as a basis. Available information of a group might be one of these attributes, so identifying the group of potential users is usually a first step, which means collecting information of user characteristics. On the other hand, our proposal adopts a methodology based on inclusive design. It does not mean that the audience will have to include all types of users, but as indicated by Keates and Clarkson [12], only those users who are targeted by the intended product. It is important, at this stage, identifying objectives and needs of the targeted users – visually impaired ones – because even they share objectives with common users, their access needs are different [14] [15].
We have built a supporting tool to facilitate the identification process. The following sections briefly describe its main steps.

2.1 Collecting User Characteristics

A basic requirement is that each system should allow to uniquely identifying each user type. In designing the user interface, a user or groups of users are described in relation to its characteristics [16]. In other words, a real user profile for an application is created to describe the users in terms of their individual attributes such as age, gender, physical abilities and even disabilities. In the context of our approach, the user's profile will include personal data obtained from information provided by the user, information captured by on-screen exercises, and technical data obtained by the user navigation. Let us further detail this profile:

- **Information provided directly by the user**. Personal data have two objectives: managing user identification through the name, surname, etc.; and allowing the user to be categorized based on authentication features such as name-username, password, IP address, etc. Besides, data provided by users allows us to capture demographic factors such as age, and language; relevant characteristics such as whether users wear glasses; and some other information of interest to the design of profiles such as knowing how much experience users have with the information technology environment, and with using assistive devices (screen readers, screen magnifiers, voice browsers, etc.). This information is provided directly by the user, through a questionnaire that must be answered at our system's registration.
- **Information captured by on-screen exercises**. This information is captured by different methods using animation images with which the user must interact. The attributes try to determine if the user is able to set the location of an object in terms of its size, color, shape, distance and mobility. These features are important because they help determine the kind of visual impairment, for example to identify the presence of color blindness. The *size* attribute relates to recognizing dominant features of figures or shapes when they appear in different sizes, textures, or positions. The *color* attribute refers to the completion of various tests to discriminate color recognition and determine whether or not a person is color blind. Here, the quickest method for diagnosis of blindness is through stained sheets of Stilling and Ishihara [17]. The *shape* attribute refers to the abilities to organize and interpret information that is seen, and makes it meaningful. The *mobility* attribute refers to the ability of the individual to recognize a moving object visually. The *distance* is an attribute that collaborates with the identification of the size of the objects.
- **User technical data**. Technical information of the user is obtained by browsing the Web. It provides technical context information with which the user accesses the Web. The attributes that will be captured by our supporting tool are: the language, the user agent or browser used, and the operating system on which the user operates.

Once established the types of features that we wanted to capture, we determined which features were relevant to our project and which not. To do this, we conducted a online survey following the proposal of Beam [19]. The survey

Fig. 1. Fragment of Web survey: exercises on the Ishihara Test

was designed for potential users of our application and in order to collect data from a representative sample of the population. We took into account factors that determine whether the user has or has not visual limitations, aiming to identifying them through some practical exercises. Figure 1 shows some of the questions.
Data collected by the survey in demographic terms (such as age and gender) can be complemented with other data of the survey, such as use of glasses, time of access to the web, types of use of the Web, etc.

2.2 Modeling User Stereotypes

User profiles are modeled based on common attributes among users [1]. But a user's preferences are highly variable, and data that make up profiles are constantly changing and adapting. That is why it is necessary to evaluate the user constantly. For this, to be useful from the point of view of Web Accessibility, we grouped users based on their access limitations, and distinguished between types of limitations and user profiles by grouping similar limitations. These classes are called *Stereotypes*. Stereotypes will be used in the context of an automatic classification taking into account the proposal of Brajnik [18]. The classes we propose are:

- **Blind users**. This category includes users without vision or with minimal light perception. This category may also include users who can see but use some disabling technology such as browsers that do not display images, voice portals, etc. These kind of users use screen readers or talking browsers.
- **Low-vision users**. This category includes users with low vision who use screen magnifiers. Often, these users only use the accessibility features of the operating system, like reducing resolution of the screen size, and increasing the source polarity levels and color contrast. This category may also include restrictive technology, such as smart phones and PDAs which reduce the screen and interaction facilities.
- **Color-blind users**. This category includes users who cannot distinguish certain colors. In some cases, these users cannot distinguish between red and green; and in some other cases between blue and yellow. This category may also include users of resources that change or reduce the color fan, for instance gray-scale screens.
- **Users with photosensitive epilepsy**. This category includes users who have photosensitive epilepsy. It triggers seizures when browsing pages with flashing lights.
- **Users without visual impairment**. This category includes users with sufficient visual acuity to identify, locate and track objects in context. It also includes people who use corrective lenses to improve their vision.

Each user profile is classified in at least one type of stereotype. Notice that some user profiles can be classified in more than one stereotype, i.e. a user can be visually impaired and also have color blindness. On the other hand, for each stereotype, we can identify user profiles that fit in.

3 Automatic Profile Generation

With the vast number of information resources available today, a critical problem is how to locate, retrieve and process information. An approach to this problem is to provide access to the large number of information sources by organizing them into a network of agents [13], where the goal of each agent is to provide information and expertise on a specific topic. These agents can be developed and maintained separately, drawing on the other available agents and providing a new information source that others can then build upon. Following this approach, we present a deliberative agent to carry out the creation and classification of the profiles of users in stereotypes, considering visual limitations that a user owns. The following subsections describe the structure of the agent and how it works for the creation and classification of user profiles. We also illustrate the agent behavior through a motivating case study.

3.1 An Agent-Based Solution

An intelligent agent defines a knowledge-based system that perceives its environment (which may be the physical world, a user via a graphical user interface, a group of other agents, the Internet, or other complex environments) [20], reasoning to interpret perceptions, inferences and solve problems. An agent defines actions, and acts on the environment to realize a set of goals or tasks for which it was designed. The agent's structure describes the interconnections among its different modules. In our case, it is a deliberative structure based on the BDI model (Belief, Desire, and Intention). This model is based on the following components:

- *Beliefs:* It includes knowledge that the agent has of itself and its environment. In our case, this component includes the metadata user profile, stereotypes and questionnaires.
- *Desires:* These are the goals that the agent wants to meet at the long term. In our case, this component includes the objective of creating a user profile classified into a stereotype.
- *Intention:* These are goals that the agent tries to achieve. In our case, this component includes the following objectives: create a user profile based on questionnaire responses and assign the profile to at least one stereotype.

The structure of the agent, called *Profile Builder Agent*, as shown in Figure 2, in addition to the aforementioned components consists of the following modules: Interaction, Reasoner, Executing, and Knowledge base.

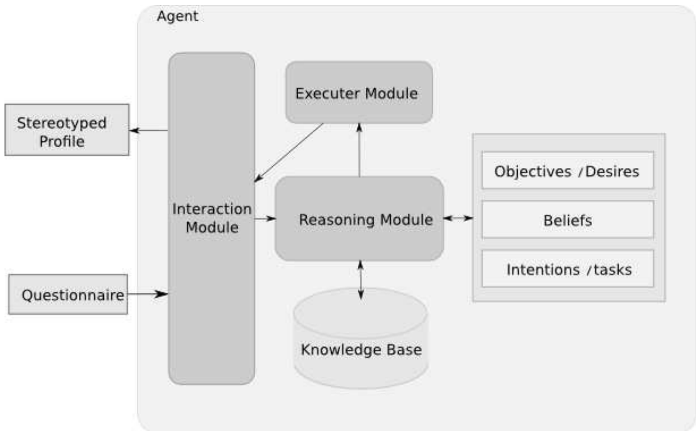

Fig. 2. Structure of the Profile Builder Agent

Since this agent is based on practical reasoning [21], it decides during each action to facilitate the achievement of the objectives.

Firstly, through the *Interaction Module*, the agent perceives changes in the environment in which it operates, identifying when there is a new questionnaire available and answered by a user. Then, the agent adds the information contained in the questionnaire to its *knowledge base*. Desires, goals and intentions

are derived from there by using the *Reasoner Module*, i.e. it creates a user profile stereotyped, taking into account the metadata of the user profile, different stereotypes and the questionnaire.
Secondly, the *Reasoner Module* takes those intentions, checks beliefs about the world based on its perception (knowledge base update), and finally selects one action to be taken (decision), reasoning about beliefs and intentions. This decision is transmitted to the *Executing Module*, which runs the selected action; i.e. it creates a new user profile and classifies it in at least one stereotype. It may produce changes in the environment, generating the order to insert the profile in the database as output. Then the agent returns to the first step, in order to perceive changes that might have occurred in its environment.
To illustrate the interplay of the agent with its environment, indicating interactions to perform a specific task, we use the sequence diagram shown in Figure 3. In this diagram, we can see that the user agent requests the Web application a registration for a user. In response to this request, the Web application transmits the user agent the questionnaire that must be completed to register a Web user. Once the user completed the questionnaire, it is stored by the database manager system receiving a unique ID. This ID allows the Profile Builder Agent to recover and process the stored data of the questionnaire, and next, to set up the corresponding stereotype. The Reasoning Module, which is a component of the agent's structure (Figure 2), is the responsible for performing this process. To do so, the Reasoning Module proceeds as follow: (i) takes into account the agents Beliefs and Knowledge Base (Figure 2), (ii) analyzes the data of the questionnaire, and then, (iii) determines the users characteristics, which include the types of users disabilities, according to the validation performed to all the answers provided by the user.

3.2 Profiling Surveyed Users

In order to evaluate our agent-based solution in a real environment, we differentiated two steps: checking the completeness of the stereotypes, and checking the behavior of the agent.

Checking the User Stereotypes Several international organizations, such as the WHO [22, 23] and the WAI[14], have studied and classified the different visual limitations that people may have. On the basis of these approaches, we defined the stereotypes of our proposal for user profiles.
To validate the completeness of the defined range of stereotypes we elaborated a Web survey, which was designed in order to evaluate that every profile was considered and that there is no respondent's profile that cannot be classified.
In addition, the same survey can confirm the accuracy of the users' answers, since it asks the user to state his/her disabilities. Then, with the various exercises in the survey, the veracity of the declarations can be checked and validated. For example, consider the case of a user who declares to have color blindness as visual impairment. To validate such a situation, we took into account the answers given by the user to those survey exercises that corroborate the presence

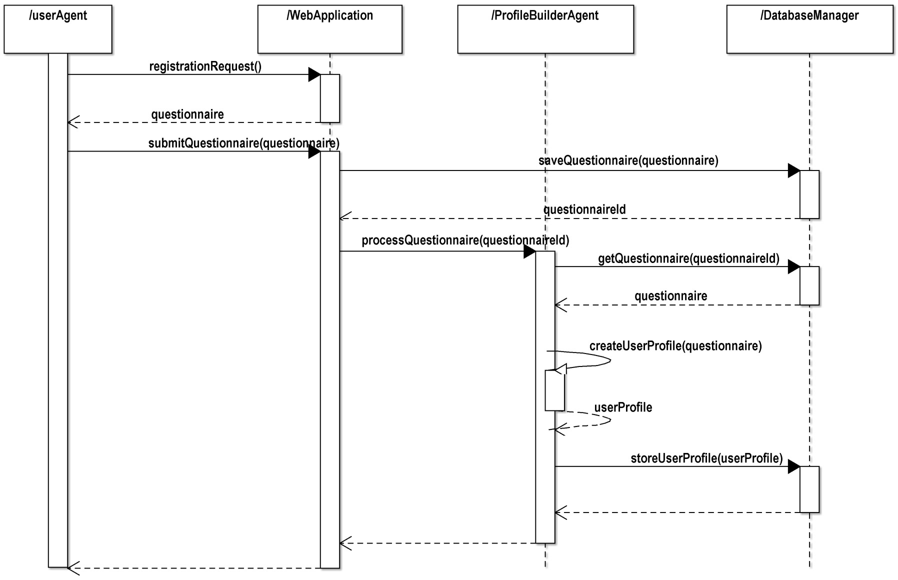

Fig. 3. Sequence diagram of the agent's interaction with its work environment

of such disability, such as the Ishihara Test templates (shown in Figure 1). Also, if a user does not state the presence of certain visual impairment, it is possible to infer the presence of such disability by analyzing the responses given to the rest of the questionnaire.
To spread the survey and collect answers, we were assisted by the Accessibility Commission of the University of Comahue[4], which was in charge of contacting visually impaired students and other users. As a result, we collected 159 answers, of which 48,42% were fully answered, and were the basis for the next checking.

Checking the Behavior of the Agent Once validated the election of stereotypes of user profiles, the results of the survey were used to train and validate the behavior of the Builder Profile Agent.
Firstly, the agent was trained by taking a set of training cases for each of the stereotypes. In this way, the agent built each user profile and classified it according to one/more than one stereotype.
Secondly, for validating the behavior itself, the sample population was used to determine the correctness of the results obtained by the agent. Thus, statistics calculated on these results must be the same as those calculated manually. To

[4] "Comision de Accesibilidad al Medio Fisico y Social" dependiente de la Secretaria General de la Universidad Nacional del Comahue

start the validation process, we used Weka[5] - a knowledge discovery supporting tool suitable for data mining. Weka offers a variety of classifiers and evaluation techniques. From them, we selected the hypothesis evaluation based on precision, where the percentage of relative error indicates how far the experimental results are from the accepted value. A learning guide was used to minimize the number of mistakes - for instance, falsely rejecting the hypothesis. In other words, we used a series of indicatives as True Positive (TP), False Positive (FP), Precision, Recall and other statistics.

Precision [25] for a class is the number of true positives (i.e. the number of items correctly labeled as belonging to the positive class) divided by the total number of elements labeled as belonging to the positive class (i.e. the sum of true positives and false positives, which are items incorrectly labeled as belonging to the class). *Recall* [25] in this context is defined as the number of true positives divided by the total number of elements that actually belong to the positive class (i.e. the sum of true positives and false negatives, which are items which were not labeled as belonging to the positive class but should have been). The precision and recall scores are combined into a single measure to obtain an overall percentage of effectiveness – this measure is named *F-measure* [25].

We used ZeroR, NaiveBayes, J48 and OneR as classification algorithms. The ZeroR classifier simply predicts the majority category (class); however it was useful for determining a baseline performance as a benchmark for the other classification methods. The NaiveBayes classifier is Bayesian network model oriented to simple classification [24]. Its main disadvantage is the assumption of independent variables, leading to a lack of precision. J48 is an implementation of C 4.5, a well-known classifier that use variable patterns to build decision trees. They are based on a dependent variable or class, and the classifier aims to determine the value of that class for new cases. Finally, the OneR algorithm is a simple, yet accurate, classification algorithm that generates one rule for each predictor, and then selects the rule with the smallest total error as its "one rule".

Table 1. Comparative table of classification using several algorithms

Classifier Algorithm	*TP Rate (%)*	*FP Rate (%)*	*Precision (%)*	*Recall (%)*	*F-Measure (%)*	*Correctly Classified Instances (%)*
ZeroR	0.457	0.457	0.209	0.457	0.287	45.7143%
NaiveBayes	0.757	0.138	0.765	0.757	0.758	75.7143
J48	0.771	0.163	0.755	0.771	0.755	77.1429%
J48 with combined attr.	0.971	0.012	0.965	0.971	0.966	97.1429%
OneR	0.829	0.141	0.733	0.829	0.773	82.8571%
OneR with combined attr.	0.971	0.014	0.958	0.964	0.773	97.1429%

[5] http://www.cs.waikato.ac.nz/ml/weka/

Table 1 shows the results after executing the classification algorithms. As we can see, the results are related to the training set, since the same data set was used both for training and classification. Firstly, the ZeroR algorithm was used as a basis for comparison because its results should be improved by any other algorithm. ZeroR classifies all data as members of the majority class. For instance, when considering our training set, the majority class is "non-disabled" and ZeroR only correctly classified 45,71% of all cases. This result was quite inefficient having a rate of 45,7% of false-positive, i.e. incorrectly classified data; and precision only reached 20,9% of the cases. On the other hand, when using the NaiveBayes algorithm, we assumed that attributes were independent from each other, i.e. there was no relation among responses. Then, although calculations from this algorithm improved classification results (for instance, precision raised to 76,5%), assuming no relation among attributes was not realistic. Therefore, to establish a better classification model, we combined some attributes following recommendations from domain experts (for instance, "use of glasses" and "type of visual impairment"). Then, when using more precise classification algorithms such as J48 or OneR, we observed a significant improvement of correctly classified cases (97,14%) with a higher precision (96,5%) and effectiveness (F-measure higher than 95%).

Figure 4 shows the resulting matrix after executing the J48 algorithm with combined attributes. Correctly classified cases are located at the diagonal. Notice that one of the misclassified cases corresponds to a color blindness user. This was due to the fact that the training set had few of these cases, so training for this visual limitation was insufficient.

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=== Confusion Matrix ===

  a  b  c  d  e   <-- classified as
 29  0  0  0  0 |  a = VisualImpairment
  0 32  0  0  0 |  b = WithoutDisabilities
  0  0  7  0  0 |  c = DontKnowNoAnswer
  0  0  0  1  0 |  d = PhotosensitiveEpilepsy
  0  0  0  1  0 |  e = ColorBlindness
```

Fig. 4. Confusion matrix of the J48 classifier algorithm with combined attributes

It is obvious that there is some interdependence among attributes of the users' profiles, and such relations should be considered when designing the agent. However, the process of combining attributes is still preliminary since it might be improved by preselecting characteristics. Results from the experiments have shown that considering redundant or irrelevant characteristics may hinder classification. For instance, information about the type of service selected on the Web (chat, navigation, etc.) is irrelevant when determining the stereotypes. A

previous selection might help to start classification with more meaningful information.
Secondly, relations among attributes should be further explored. For instance, the use of glasses indicates the fact that some visual limitation is been treated; or the results of the Ishihara test indicates a color blindness situation (even thought that this person does not declare it explicitly).

4 Conclusion and Future Work

We have introduced a proposal to automatically identifying characteristics of visual-impaired users as user stereotypes. The approach relies on collecting cases by using a questionnaire, which are the training basis for an intelligent agent. Automatically classified profiles might be an interesting achievement, for instance as a starting point to automatic web accessibility repairing.
We have shown a first step. However, it needs further experimental validation as well as extensions to relate profiles to web accessibility recommendations, such as the Web Content Accessibility Guidelines. Our current efforts are addressed to these aspects, aiming at facilitating the process of making the Web accessible for all.

5 Acknowledgments

This work is partially supported by the UNComa proyect 04/F001 “Reuso Orientado a Dominios”, under the program “Desarrollo Basado en Reuso”, and the PAE-PICT 2312 project.

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