User Centered and Context Dependent Personalization Through Experiential Transcoding

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***Abstract*—The pervasive presence of devices exploited to use and deliver entertainment text-based content can make reading easier to get but more difficult to enjoy, in particular for people with reading-related disabilities. The main solutions that allow overcoming some of the difficulties experienced by users with specific and special needs are based on content adaptation and user profiling. This paper presents a system that aims to improve content legibility by exploiting experiential transcoding techniques. The system we propose tracks users' behaviors so as to provide a tailored adaptation of textual content, in order to fit the needs of a specific user on the several different devices she/he actually uses.**

Keywords-device capabilities; content adaptation; user profiling; legibility; reinforcement learning

I. INTRODUCTION

The wide diffusion of smart objects in everyday life has to deal with the increasing use of digital contents and specifically digital text. Smart TVs, eBooks, tablets, smartphones and the new generation of smart appliances are just examples of current devices exploited to manage and enjoy digital contents. Since these devices and the related services are pervasively diffused, a part of potential users have to cope with an increasing difficulty in reading and really enjoying text provided by such systems. Even smart devices devoted to delivery multimedia content (such as smart TVs) do a large use of text-based interfaces to support users in browsing, searching and selecting contents.

Reading disabilities, vision impairments and difficulties experienced by elderly people can't easily cope with the wide range of different screen sizes and capabilities that characterize the Internet of Things. In fact, digital text characteristics, users' abilities and device capabilities concur in affecting both readability and legibility of textual content. Thus, transcoding and adaptation activities can be performed in order to make such contents more legible and readable to users with disabilities and to users equipped with different devices.

The main aim of our work is to improve legibility by adapting some text formatting characteristics (i.e., font size, font face, luminance contrasts, and so on) according to users' needs and device capabilities. Our work focuses specifically on Web contents, but we are extending it to manage PDF documents and other structured open formats.

In this paper, we propose an innovative adaptation system, called ExTraS (EXperiential TRAnscoding System [1]) based on the concept of experience-based transcoding. Usually, traditional content adaptation mechanisms categorize users' needs and/or device capabilities on the basis of a pre-defined set of classes. Differently, experiential transcoding adapts content by tracking each single user's experience and behavior and by providing content tailored to him/her.

We have considered the adaptations of text formatting characteristics (such as font size, font type, spacing, color contrast, etc.) that help users in improving content legibility. They strongly depend from the reading difficulty experienced by the user; in fact, an adaptation needed by a user could be counterproductive for another one. With the aim of doing a strong personalization on the basis of user's needs, we decided to let the users adapt those Web page elements which represent an actual barrier for them, instead of automatically adapting the entire Web page. This avoids significant layout distortion, and, at the same time, it gives emphasis on those elements that the user selects. Automatic adaptations are performed on the basis of a user profile that keeps track of the his/her needs, taking into account both the device in use and the user's experiences and behaviors, so as to provide a context-dependent adaptation. The adaptation is based on a machine learning mechanism (Reinforcement Learning) that is based on the idea of reward/punishment. We have built a prototype system and performed a simulation assessment that confirms the viability of our proposal.

The remainder of the paper is organized as follows. Section II describes related work, while Section III presents the how our system profiles users by learning preferences from their behaviors. Section IV introduces the prototype we have developed while some results are reported in Section V. Finally, Section VI concludes the paper illustrating main conclusions and further work.

II. Related Work

Our work is mainly based on different topics, which are briefly described in this section:

- Improving Web pages legibility, by providing text characteristics adaptations.
- Adaptation of those elements that present some barriers to users, instead of transforming the entire Web page.
- Definition of standards for users and devices profiling.
- Experiential transcoding and adaptation based on users' behavior.

A. *Improving Web pages legibility*

Legibility is related to perceiving text by distinguishing letters, while readability is related to reading and understanding textual information [2, 3, 4]. It is worth noting that text formatting characteristics can strongly affect enjoying reading [5, 6]. Aspects of text formatting that users may need to adapt are: font face, text size, background and text colors, line height, words and letters spacing, text alignment. Several studies have been done to identify which settings better support users according to their specific reading abilities [7], by considering that they may change according to:

- the device in use, including eBooks, tablets, smartphones [8], smart TVs [9] and ATMs [10];
- users' specific needs, such as the ones related to the context of use [8] and the ones related to specific users' conditions (including reading disabilities [4, 11] and ageing [5]).

Outcomes from all these previous studies have been taken into account in our work.

B. *Elements adaptation on demand*

Some eAccessibility studies have emphasized the importance of adapting only those parts of content that represent an effective barrier to users. This way, the whole content and its layout are not distorted, and customization is just limited to those elements that really affect users' reading.

Rello et al. [12] have developed a cross-platform application, which can let users ask for synonyms of difficult words. The idea is that users can adapt Web content by choosing more understandable words, making the page more readable. In particular, the application has been designed to meet the needs of mobile users with dyslexia and it has been tested on real cases.

Watanabe et al. have presented a Web content adaptation tool for assisting low literacy readers to access online information in [13]. Their approach is similar to [12]: proposing synonyms to difficult words and additional (visual) information when it is necessary, on the basis of users' requests.

Our approach follows the same idea (but it is not limited to a specific disability): users can choose which elements really affect their ability to read (even on the basis of the device in use). Our system adapts those elements which represent a barrier, without the need of changing the whole Web page. Moreover, our system tracks users' behavior and it learns which elements have to be adapted and which characteristics have to substitute the discarded ones.

C. *Profiling Users' preferences*

There are several systems that use different types of user models and profiles. In particular, XML and RDF-based standards have been used to profile users and meet their needs in particular conditions, for instance when they access content via some mobile devices, or if they present some disabilities. The most common standards are: Composite Capabilities/Preference Profile (CC/PP) and User Agent Profile (UAProf) to profile device capabilities, ACCessibility Learner Information Package (ACCLIP) and ISO Personal Needs and Preferences (PNP) to profile users' needs in terms of accessibility. A brief comparison among them can be found in [14].

Some works have been done to combine and exploit such standards [14, 15, 16]. In particular, this last paper proposes a user profile model which gathers static and dynamic data describing the user, the device in use and the context. Such a kind of profile is exploited in an IPTV streaming use case.

Similarly, in our system, we have taken into account well-known profiling standards (which are extendable) so as to provide a standard-compliant profiling system.

D. *Experiential transcoding*

Web pages transcoding and adaptation have been strongly exploited in many research systems; their use was usually driven by the categorization of device capabilities and users' needs [17]. A novel adaptation approach, called "experiential transcoding" [18, 19], exploits the concept of experience-based transcoding. Compared with more traditional forms of Web transcoding and adaptation, the main advantage of experiential transcoding is that it is strongly user-centered. It applies techniques and mechanisms which adapt contents on the basis of users' experience. In particular, in [19], eye tracking has been used to understand users' experiences.

Users' behaviors as personalization-drivers have been exploited in [20]; in this case, the author proposes a novel approach to construct a dynamic user model, strongly based on user's behavior, which drives the personalization of media augmentation, accessed by using some mobile devices.

Analogously, our work exploits the idea of adapting Web contents on the basis of users' experience. In particular, we track past users' adaptations so as to learn users' preferences and to provide (and/or suggest) adequate personalization. This approach has been inspired by recommendation systems used in e-commerce Web sites, social networks, search engines, etc. A similar approach has been used in [21], where the authors exploited a reinforcement learning algorithm in order to customize the rendering of advertisements in Web pages, on the basis of users' preferences.

III. PROFILING USERS FROM USERS' BEHAVIOR

In order to track user's experience and to learn his/her preferences (predicting his/her needs), we have used a machine learning algorithm, based on the Reinforcement Learning concept and on the idea of reward/punishment [1].

Our user's profile is a collections of textual characteristics (which can affect content legibility) gathered by the system. Such a profile is shared among all the devices the user exploits and it takes into account user's needs. The system computes automatic adaptations and related reward/punishment values, according to user's behavior. Periodically, the user's profile is updated, by adding new characteristics or by computing new reward/punishment values.

The system learns user's preferences in terms of discarded and chosen text formatting characteristics: it punishes the discarded ones, while it rewards characteristics the user has requested through the adaptations. Obviously, the user's profile will become more accurate the more the user asks for adaptations.

We have designed an XML-based profile which is structured in different parts, according to the devices the user exploits. In each of these parts, the system stores text characteristics (as tags) the user has asked for adaptations or the user has discarded, the related value (as the "**v**" attribute) and a number, as the "**w**" attribute. Such a number states the reward/punishment related to the adaptation asked by the user. In fact, the "**w**" value varies according to user's behaviors (Table 1). The absence of a characteristic or of a specific "**v**" value means that the user has never asked for such characteristic adaptation or he/she has never discarded or chosen such a "**v**" value.

In ExTraS, no initial profile is provided, but this is automatically created and fed by our system, as the user explicitly requests for adaptations. A detailed example of our user's profile can be found in [1].

In order to learn such users' preferences, our system has been modeled by using the Reinforcement Learning concept. The adopted learning algorithm is Q-learning [22]. The whole system works as follows:

1. when the user opens up a Web page, the system parses textual characteristics, taking into account the user's profile.
2. If there are some characteristics the user has discarded (with a negative "**w**" value in the profile), then the system decides if automatically adapting such characteristics, by substituting them with the ones the user prefers (with the highest "**w**" values) or just proposing such adaptations. If $t < w < 0$ then the system just proposes the adaptation, while if $w < t$ then the system automatically adapts such a characteristic, where **t** is a specific threshold. Such a threshold is a negative integer which can be differently set for each characteristic.

TABLE I. RELATIONSHIPS BETWEEN "W" AND USER'S BEHAVIOR

W value	User's behavior
w<0	The user has discarded the related "**v**" value
w>0	The user has chosen the related "**v**" value
w=0	The "**v**" value related characteristic has obtained the same quantity of rewards and punishment

3. Then the user exploits the Web page with a specific set of characteristics: font size and face, spacing, alignment, background and foreground colors, etc.
4. In case of automatically performed adaptations, if the user ignores them, then the related reward is +1. Else, if the user rejects them, then the punishment is -1.
5. In case of proposed adaptations, if the user accepts them, then the related reward is +1. Else, the punishment is -1.
6. If the user applies an adaptation to an element, the system assigns +1 to the requested characteristic and -1 to the discarded one. Unchanged characteristics receive no reward.
7. Updated rewards and/or new characteristics (chosen and/or discarded for the first time) are stored into the user profile.

A use case of this algorithm at work is presented in [1].

IV. PROTOTYPE

We have designed and developed a prototype (implemented as a Firefox extension by means of Mozilla SDK) which adapts HTML documents. Our system is structured in three modules: the Profiling Module, the Learning Module and the Adaptation Module, as depicted in Fig. 1.

The adaptation process is locally performed on the client side. Adaptations are computed by transcoding tags, attributes and related values: the system injects new tags or attributes and/or it substitutes original tags or attribute values with customized ones. Users can use a contextual menu to set adaptations on an HTML page.

Fig. 2 shows the ExTraS prototype running on a Samsung Galaxy Tab 2 equipped with Android 4.0.4 and Firefox 21.0. In particular, this figure depicts the contextual menu used to let the user adapt the specific element of the page. It makes possible to zoom in, to zoom out, to change the font family, to change the background and foreground colors on the element the user has chosen.

The prototype performs the requested adaptations by suitably transcoding the HTML and/or the CSS code of the page. In the meanwhile, the system tracks users' behaviors, with the aim of learning their preferences and then automatically applying or proposing suitable adaptations.

When a user opens up a Web page, then the system parses the DOM and the related style rules, taking into account the user's profile and, in particular, those characteristics with a negative "**w**" value, so as to decide which adaptations automatically applying or proposing.

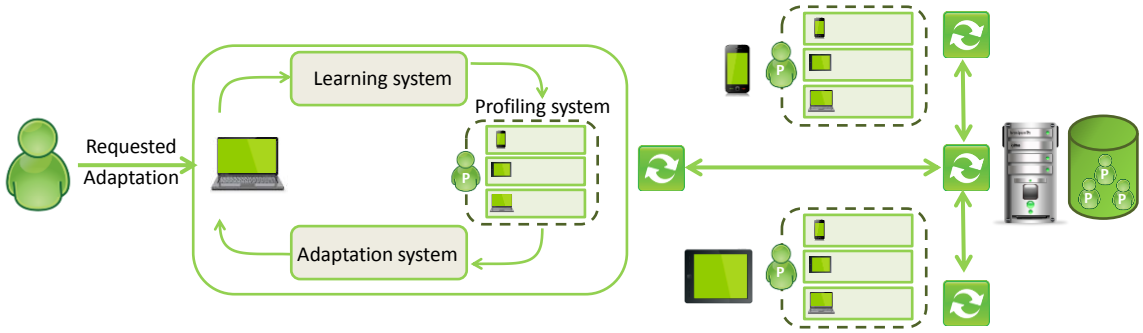

Figure 1 - The whole system architecture.

Each user stores his/her profile structured in device related sections, on each device he/she is using. Updates to the user's profile are locally stored (on the device in use) and a synchronization mechanism is needed to spread such updates on the other copies of the profile. The copy of the profile stored on the server will be used in case of new devices associated to a same user: when a new device joins the system, the user's profile will be downloaded from the server and a new profile section will be added to all the copies of the profile, via the synchronization mechanism.

V. Experimental Evaluation

To assess the performance of the proposed approach, we built a simulation scenario. The simulator is written in Java language and it is able to mimic the behavior of different users, who are surfing the Web with different type of devices. In particular, we have modeled a user with dyslexia equipped with a PC and an elderly user equipped with a tablet. Of course, the simulator can be extended to other contexts. We have considered that these two users access Web pages by means of a browser running our prototype, enabling and disabling the Learning Module. This means that we have simulated four different types of contexts.

The simulator mimics a user behavior, browsing the Web among a set of the 10 most visited pages, taken from the Alexa top Web sites list, according to ranking data they have gathered in May 2013 [23]. The set of Web pages was: Facebook news, Facebook user's wall (http://www.facebook.com), Google home page, Google search page (http://www.google.com), Yahoo! home page, Yahoo! result page (http://www.yahoo.com), Wikipedia home page, Wikipedia item page (http://wikipedia.org), Youtube home page, Youtube video page (http://www.youtube.com). At each simulation time step, the user starts working on a different Web page; we considered a browsing activity of 20 time steps for each single user. 20 users were generated for each of the four context types (80 users totally). We present here the average results.

Each user has its own characteristics, grouped as a profile, corresponding to the most typical preferences that users might want when accessing a given content, according to the literature [5, 11]. During the simulation, we considered the following preferences for each user, to be associated to the text elements of the Web pages. We assume that a user with dyslexia commonly prefers to read text with an Arial font, or a San Serif font family. He/she prefers that text elements are displayed with a font size equal or higher than 18 points. As concerns the text alignment, a left alignment is preferred while a justified alignment is highly deprecated. The favorite background color is crème, and the foreground one is black [11]. An elderly user, instead, benefits from San Serif type fonts; font size should be around 16-18 points. A left alignment is preferred, with a line height set to 1.5. The suggested color contrast is high [5].

In this evaluation, we assess how many times the user is forced to manually act on the Web page, when:

- an adaptation system is available, that allows to adapt elements of a Web page, based on direct and manual requests by the user; or
- an automatic adaptation system performs these transcoding activities, based on past decisions of the user, each time a user selects a given element to focus.

We stress the fact that this work focuses on the idea of adapting single elements, based on the particular preferences of the user, that can vary based on their characteristics. This in order to avoid that an entire Web page is adapted automatically, thus altering its layout significantly, and also giving emphasis on those elements that the user selects. As an example, consider Fig. 3 which shows preferences related to a user with dyslexia applied to the whole Yahoo! home page (retrieved on 22nd August 2013). Fig. 4 depicts the same page shown in Fig. 3, with a set adaptations performed by a user interested in reading titles and some main features.

To simulate such partial adaptation of the Web page, we introduced two parameters: ρ and γ, where $0 < \rho+\gamma \leq 1$. We assume that the user reads, for sure, a portion γ of the page, while only a random part ($\rho \geq 0$) of the remaining portion ($1-\gamma$) of the page is read (and thus adapted, when needed). Hence $\rho+\gamma$ represents the portion of the page the user reads: when $\rho+\gamma = 1$, the user reads the whole page. If $\gamma = 0$, a completely random number of elements composing the Web page is selected to be adapted. Setting $\gamma > 0$ allows to simulate those situations when a given portion of the page contains the main contents that are to be visualized and read by the user. Stated simply, the higher is γ and the higher is the number of elements that the user reads (and adapts).

Fig. 5 shows the average amount of manual clicks, intended as user's requests to adapt a given element, measured during the simulations, changing γ value from 0 to 0.5 and ρ is a random value ranging from 0 to $1-\gamma$. This

average number of clicks has been computed taking into account all the 20 timesteps for each one of the 80 simulated users. In this plot, the average number of clicks is shown with a logarithmic scale, grouped by the four context types. For the sake of simplicity, we have considered a very low threshold *t*, for consistent users, who accept the adaptations the system proposes or automatically performs. As we expected, the manual adaptations done by users equipped with the Learning Module is significantly lower than the activities requested to users who are not exploiting it, independently from the portion of read page. Conversely, a very high number of clicks is required when the Learning Module is not active: in this case the higher is γ and the higher is the number of manual clicks. Moreover, the context do not influence the number of clicks when the Learning Module is active (in fact, the two related lines are almost overlapped, since the differences among those average numbers of clicks are minimal), while there is a significant difference among users with dyslexia and ageing users clicks when the system does not track users' behaviours and does not learn their preferences. This means that our system is effective only when a learning machine mechanism is provided; otherwise, the high numbers of clicks would discourage users in using it.

Fig. 6 shows the clicks measured during a single simulation for each of the four contexts. It is possible to appreciate how the users equipped with our Learning Module need a very low number of manual clicks.

An evaluation phase with real users should be conducted so as to understand their appreciation of our system and to test the amount of activities they are ready to perform in order to obtain Web pages with adapted elements, before the system learns their preferences. Furthermore, different learning machine mechanisms should be adopted and tested, in order to identify the most effective one for our system. Finally, more tests should be conducted with different t threshold values and with different levels of consistence in users (how often users reject proposed or automatically performed adaptations), so as to define a suitable t values for each adaptable Web page element.

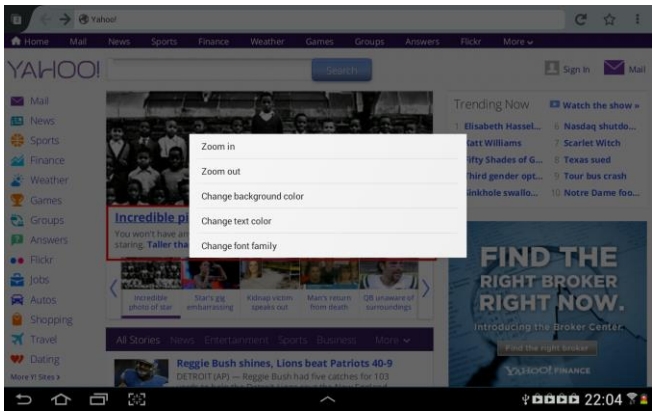

Figure 2 - A screenshot of Yahoo! with our contextual menu.

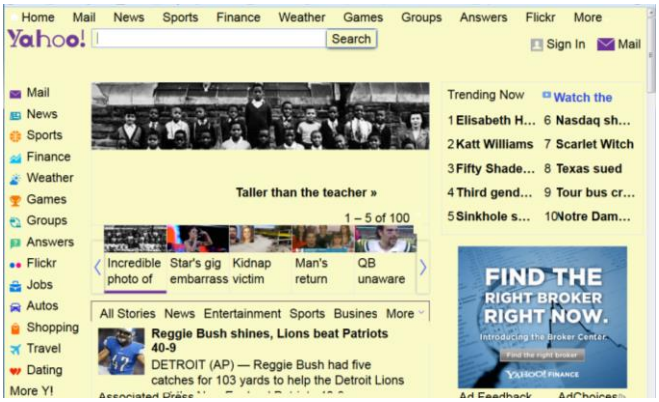

Figure 3 - A screenshot of Yahoo! with the all adaptations performed.

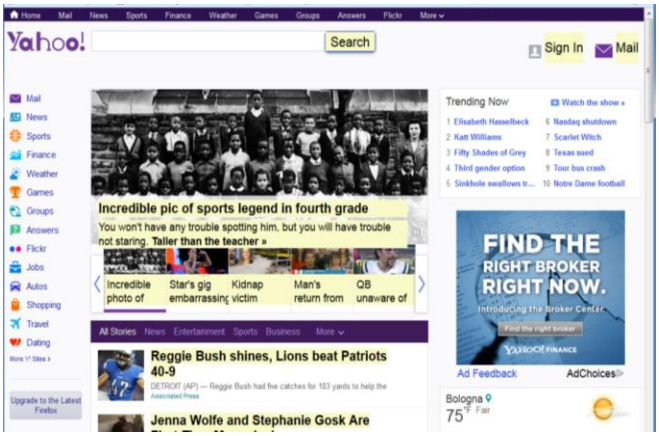

Figure 4 - A screenshot of Yahoo! with some adaptations performed.

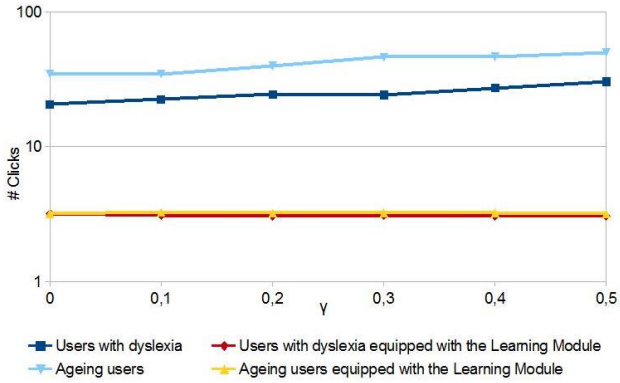

Figure 5 - Average number of clicks per page.

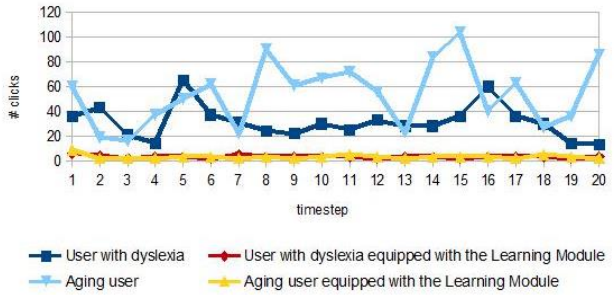

Figure 6 - Number of clicks during a single simulation.

VI. CONCLUSION

Our work on improving Web pages legibility by means of experiential transcoding (learning user's profile from his/her behavior) is still under development. The goal of the system we have presented is to customize Web pages according to users' needs and capabilities of the device in use. Hence, it automatically provides the best adaptations, tailored for each specific user, on the basis of the exploited device (PC, tablet, smartphone, smart TV, etc.).

We have assumed that adapting some elements of the Web page is more effective than altering the whole page layout. We have presented simulation results, showing that users take advantages from the adaptations automatically performed by our system, as a consequence of the learn user's preferences.

A testing phase with real users is needed. We are now planning a campaign with users with reading related disabilities and users equipped with different mobile devices.

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