Predicting User Interface Preferences of Culturally Ambiguous Users

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Abstract
To date, localized user interfaces are still being adapted to one nation, not taking into account cultural ambiguities of people within this nation. We have developed an approach to cultural user modeling, which allows to personalize user interfaces to an individual's cultural background. The study presented in this paper shows how we use this approach to predict user interface preferences. Results show that we are able to reduce the absolute error on this prediction to 1.079 on a rating scale of 5. These findings suggest that it is possible to automate the process of localization and, thus, to automatically personalizing user interfaces for users of different cultural backgrounds.

Keywords
Cultural Usability and Internationalization, User Modelling, Personalization, Cultural Adaptivity

ACM Classification Keywords
H5.2. Information interfaces and presentation (e.g., HCI): User Interfaces.

Introduction
With much research demonstrating considerable increases in efficiency when software is used within an individual's cultural frame, software manufacturers

have begun to adapt their products to foreign markets. Yet to date, this internationalization and localization of user interfaces is usually restricted to one interface design per country. Researchers have not provided much more information: So far, most studies have concentrated on a one-to-one mapping of certain user interface preferences to a whole nation, investigating differences in user interface perception or software development. If a company plans to extend their website's target group from Americans to Chinese users, for example, they can easily follow the results of these studies and design a localized Chinese version. In many cases, this will work fine. However, culture, by definition, cannot be rigidly mapped to one nation. Likewise, we cannot assign a predefined localized layout to all people of this nation, as some might have many cultural influences and are, therefore, culturally ambiguous [11].

In order to overcome this problem we have developed an approach to cultural user modeling, which allows to personalize user interfaces to an individual's cultural background. Because people cannot be expected to explicitly know their preferences to manually adapt their interface [9], our aim is to predict their preferences by calculating their cultural background based on their varying cultural influences. The goal is to develop a culturally adaptive interface that automatically adapts itself to the user’s (cultural) needs. Here, we focus on the following questions:

1. Can we predict the user's preferences by classifying her cultural background?
2. What is the preference prediction for culturally ambiguous users?

Specifically, we conducted a survey to elicit subject’s cultural backgrounds as well as preferences and evaluate how our approach was able to predict those preferences based on the cultural backgrounds.

In the following, we give a short introduction on related work and present our own advances towards cultural user modeling. We will then introduce our survey, its evaluation and results, before closing with a discussion of our limitations and future work.

Related Work (and how we extended it)

Considering culture for the automatic personalization of user interfaces is a new approach. It is based on research into internationalization and localization, as well as on user modeling for personalization.

Internationalization and Localization

In studies on internationalization and localization, researchers have analyzed differences in the design of user interfaces by different cultures [4, 19]. Others have concentrated on different cultural preferences in using these interfaces [1, 16]. The latter includes reports on mapping the cultural classification of Hofstede [7] onto user interface design: several studies have shown how his five cultural dimensions, which classify a person's cultural background into certain scores, relate to certain aspects of a user interface [3, 8, 11, 17]. The results have also shown how the dimensions influence the user's preferences [10].

Drawing on the reported influence of Hofstede's cultural dimensions on user interfaces we compiled adaptation rules that translate a user’s position in the cultural dimensions into changes of the user interface. The rules, e.g., hold information about the kind of navigational support, the level of hierarchy in the information presentation, the information density, and the amount of guidance provide. Note that these rules are used for the initial adaptation, and do not include further refinements of the user's culture.

User Modeling

User modeling has become a popular instrument to increase market share by adapting online content and services to respond to different user interests. In contrast, the personalization of both content and user interface constituents has mainly been a theoretical issue in research, for example to meet the requirements of different learner types in e-learning applications [2, 6], or the special needs of disabled persons [18]. Up to today, most approaches employ application-specific user models. Efforts towards distributed and reusable user models have been made with the help of ontologies [5, 12]. These enable the extension of numerous applications and devices, and could thus be crucial for a holistic usability.

We have developed a cultural user modeling ontology (CUMO) that factors various influences into calculating the user's cultural background (see [15]) and can be easily used to extend user modeling ontologies such as presented in [5] into an integrated user model.

Calculating the User's Cultural Background

Our approach utilizes an algorithm to calculate the user's dimensions. In order to minimize long-winded collection of assumptions about the user's preferences, we use a questionnaire when employing the user model for the first time. CUMO allows the storage of detailed information regarding influences on the users' culture, such as their parents' nationality, the religion or the highest level of education [15]. However, we reduced the explicit acquisition to the most important information that is needed for calculating a user's dimensions: The current and former countries of residence, as well as the duration spent at these places. These parameters allow us to calculate the specific influence of each country on the user's culture:

$$influenceOfCountry_N = \frac{\text{monthly duration of stay in country } N}{\text{age in months}}$$

With the help of Hofstede's five dimensions for each country, we can calculate the user's score in each dimension *H* (where *H* is one of Hofstede's 5 dimensions; *N* the number of countries that influenced the user, and $countryScore_i$ is the country's score in the dimensions):

$$userDimScore_H = \sum_{i=1}^{N} countryScore_H * influenceOfCountry_i$$

Using the $userDimScore_H$s for a user we can look up the specific adaptation rules that serve as triggering events to adapt certain parts of the interface.

The approach is based on two assumptions: Firstly, it predicates that previous studies on the influence of Hofstede's dimensions on user interface perception have been broadly accurate. Secondly, it assumes that an individual's score can be calculated by weighing the score of all relevant countries by his/her length of stay. The following section presents the preliminary results of a survey conducted with the goal of testing these assumptions.

Evaluating the Prediction of User Interface Preferences

To evaluate the prediction quality we designed a survey. Based on the adaptation rules, we developed 45 questions covering 22 general user interface preferences. Each question was asked in both a negative and positive form in order to detect outliers

Table 1. The countries that were specified to be current residences. Number of respondents are shown in brackets.

Austria (2)
Belgium (1)
China (2)
France (1)
Germany (2)
Norway (1)
Rwanda (12)
Switzerland (8)
United Kingdom (1)

Table 2. The countries that were specified to be former residences for a minimum of one month time.

Australia	Nepal
Bolivia	Norway
Brazil	Reunion Island
Congo	Rwanda
Denmark	Senegal
France	Singapore
Germany	South Africa
Ghana	Spain
Greece	Sweden
Hong Kong	Switzerland
Iceland	Tanzania
India	Togo
Israel	Uganda
Mauritius	United Kingdom
Mexico	USA

and incorrect answers. One preference required a third, paraphrased question for disambiguation. The questions covered all aspects of the adaptation rules, such as the preferred kind and level of navigational support, or the favored form of information presentation. All questions were asked in English.

Answers had to be given a rating on a scale from 1=strongly agree to 5=strongly disagree. Furthermore, the survey consisted of questions about current and former residences as well as their durations (in months), the respondent's age, highest level of education, parents' nationality, languages spoken, religion and political orientation. For statistical purposes, we also asked about the occupation, English proficiency, computer skills and the frequency of computer use. A pilot version of the survey was tested with four subjects. With the pilot we detected ambiguities in the questions and adapted the survey accordingly. The survey was then released online. Respondents were sent a link to the survey and an explanation of the survey's purpose. An incentive for serious participation in the survey was a drawing subsequent prize-drawing.
We evaluated 30 surveys to ascertain first trends. A further 16 surveys had to be discarded because answers were incomplete, or two questions covering the same preference were answered with the same rating, indicating a careless handling of the survey. All respondents specified a very good or good understanding of English. Also, the frequency of computer usage was relatively constant for all respondents: 13% of all participants specified to use the computer four to six days a week, while a vast majority of 87% uses it daily. Furthermore, most respondents (80%) were classified as culturally ambiguous because they have lived in different countries (see Tables 1 and 2).

Data Analysis
We have analyzed the data in three steps:
1. Algorithm: The information about current and former residences was used to determine a subject's dimensional scores (see previous section). Instead of actually adapting an interface, we listed the adaptation rules that would normally have been triggered.
2. Prediction: Based on the adaptation rules, we calculated the predicted answer for each question (e.g. a high score in one dimension triggered a rule that would predict a high preference for hierarchical arrangement of information).
3. Comparison: We compared the prediction (discretized to the 5 point scale) with the users' answers and noted the absolute error (AE) for each question.

Results
The analysis of the user's answers showed that on average our prediction was correct for 13 out of 45 questions. In 16 cases we were able to predict the answer with an AE of 1, in 10 cases with an AE of 2. An AE of 3 (3.5 questions on average) and 4 (0.3 questions on average) occurred very rarely. Figure 1 shows the distribution of the mean AE of our predictions. The resulting AE of only 1.079 indicates a strong correlation between the user's cultural background and the user preferences.
This result is further supported by the finding that respondents with similar scores provided similar answers. In particular, preferences of different nationalities were consistent with respect to observations made in previous studies. Respondents,

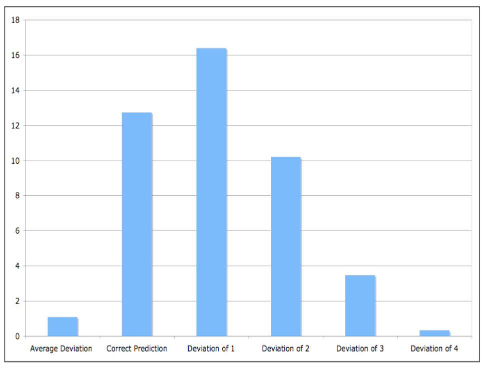

Figure 1. The deviation in predicting the user preferences from the actual answers given in the survey.

whose scores lay in a similar range to the Chinese dimensions, for example, also showed the same preferences as in the study from Rau and Chen with Chinese subjects [13]. Likewise, the preferences of respondents whose scores were similar to the dimensions for East Africa showed good consistency with our study about Rwandan preferences [14]. An additional aspect is that the vast majority of answers from respondents with similar dimensions lay within two neighboring answer possibilities. A variance of such a low extent can be rated as personal propensities that once more supports our hypothesis of a smooth transition between cultural and personal preferences. Some questions, however, lead to a high divergence of answer possibilities even though respondents had a similar predicted answer. We will have to further evaluate the reasons for these divergence in the future. Respondents usually indicated a strong preference for the appearance of the user interface. In particular, respondents with strongly differing scores also answered differently. Another group of questions, however, was answered with the same tendency even though the predictions forecasted differences. This could imply that some interface aspects are understood in a similar way by (web-literate) people from different cultural backgrounds. Whether this finding is only true for people with a high frequency of computer usage, as applicable to all our respondents, has to be subject to further investigation.

Improvement of Results

Our AE of 1.079 has demonstrated a fairly good prediction of cultural preferences. However, after including other influencing factors on the user's culture (as they are provided in CUMO) into some randomly chosen respondents' profiles, we were able to reduce the AE by approximately 0.3. For example, we included factors such as a differing nationality of the parents to the place where the respondent spent most of his lifetime. Whereas our calculation was supported by common sense to estimate how much this differing nationality could have influenced the respondent's cultural background, the algorithm has to be fed with a certain percentage. Our suggestion here is that a refinement made by the user by deciding about this percentage himself seems to be a good way to improve the calculation of his cultural background.

In search of refinement possibilities, we also looked at the adjustment of predictions with machine learning techniques. As previously mentioned, subjects with a similar score for a certain dimension usually provided similar answers for questions covering this dimension. This suggests that an adjustment of the predictions (and, thus, the adaptation rules) by learning about the actual user preferences is likely to improve the prediction for users with similar scores. Following this idea, we have evaluated the survey a second time, grouping respondents with similar dimensions. To predict the answer of one group member we averaged the answers of all the others. This lead to an AE of 0.6.

Limitations and Future Work

Our findings confirm the idea that a user's cultural background is a good source to predict user interface preferences for an initial adaptation. However, textual questions in a survey can not convey the richness of a user interface. Our survey was, therefore, only a first evaluation to confirm if one can calculate preferences for culturally ambiguous users. The next step is to evaluate these findings with the help of a culturally adaptive web application.

Conclusion

With the survey presented in this paper we have extended and verified existing research on mapping the cultural classification of Hofstede to user interface design. The analysis of our survey indicates that our method is suitable for predicting user preferences. With 80% of respondents being classified as culturally ambiguous, we were able to verify our algorithm that factors various cultural influences to calculate a user's personalized dimensionality scores. While we were not able to predict all user preferences with our user interface adaptation rules, we still achieved an AE of only 1,079. This result demonstrates that our approach is potentially powerful. We also indicated that the use of machine learning seems to further enhance our prediction. With these findings, we have taken a step in the direction of automating the process of localization and, thus, towards automatically personalizing user interfaces for users of different cultural backgrounds.

References

[1] Badre, A. The Effects of Cross Cultural Interface Design Orientation on World Wide Web User Performance, Georgia Institute of Technology, 2001.

[2] Dolog, P. and Nejdl, W. Personalisation in Elena: How to cope with personalisation in distributed eLearning Networks, 2003.

[3] Dormann, C. and Chisalita, C. Cultural Values in Web Site Design, Proc. of 11th ECCE, 2002.

[4] Gould, E., et al. Applying Culture to Website Design: A Comparison of Malaysian and US Websites, IPCC/SIGDOC, 2000.

[5] Heckmann, D., et al. GUMO - the General User Model Ontology. *10th Int. conf. on User Modeling*, (Edinburgh, UK, 2005), Springer, 428-432.

[6] Henze, N. Personalization Services for e-Learning in the Semantic Web. *Proc. of 2nd Int. Workshop on Adaptive Systems for Web-Based Education: Tools and Reusability*, The Netherlands, 2005.

[7] Hofstede, G. *Culture's Consequences: Comparing values, behaviours and organisations across nations*. Sage Publications Inc., 2003.

[8] Kamentz, E. Adaptivität von hypermedialen Lernsystemen, Universität Hildesheim, PhD thesis, 2006.

[9] Kobsa, A. User modeling: Recent work, prospects and hazards *Adaptive user interfaces: Principles and practice*, North-Holland, 1993, 111-128.

[10] Marcus, A., Cross-Cultural User-Interface Design. *HCII*, USA, 2001.

[11] Marcus, A. Cultural Dimensions and Global Web Design: What? So What? Now What? *6th Conf. on Human Factors and the Web*, USA, 2001.

[12] Mehta, B. and Nejdl, W. Intelligent Distributed User Modelling: from Semantics to Learning. *UBIDEUM* Greece, 2007.

[13] Rau, P. and Chen, Y., A Study of Culture Differences for Browsing Hypertext on Handheld Devices. HCII, Greece, 2003).

[14] Reinecke, K. A Learning Platform for the Education of Agricultural Advisors in Rwanda, Diploma Thesis, University of Koblenz, 2005.

[15] Reinecke, K., et al., Cultural User Modeling With CUMO: An Approach to Overcome the Personalization Bootstrapping Problem. in *Workshop on Cultural Heritage on the Semantic Web, International Semantic Web Conference*, Busan, South Korea, 2007.

[16] Sheppard, C. and Scholtz, J., The Effects of Cultural Markers on Web Site Use. *Proc. of the 5th Conference on Human Factors and the Web*, USA, 1999.

[17] 17. Smith, A. and Chang, Y., Quantifying Hofstede and Developing Cultural Fingerprints for Website Acceptability. in *Designing for Global Markets 5: Proc. Fifth IWIPS*, Germany, 2003, 89-102.

[18] Stephanidis, C., et al. Adaptable and Adaptive User Interfaces for Disabled Users in the AVANTI project. in *Proceedings of the 5th International Conference on Intelligence and Services in Networks,* 1998, Springer, 153-166.

[19] Yeo, A. World-Wide CHI: Cultural User Interfaces, A Silver Lining in Cultural Diversity. *SIGCHI Bulletin*, *28*. 4-7.