A Context-aware Model for the Analysis of User Interaction and QoE in Mobile Environments

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***Abstract*—This paper describes a novel approach to model quality of experience (QoE) in mobile environments. A meta-model is created to establish a set of parameters to dynamically describe the interaction between the user and the system, as well as the context in which it is carried and the attractiveness of that process. A uniform representation of user-system interaction in mobile contexts is provided. This helps user-related applications to determine QoE of users, and allows the comparison between different interaction records. Its run-time nature also allows context-aware applications to make model-based decisions in real-time to adapt themselves, and thus providing a better experience to users. As a result, this meta-model provides unified criteria for the inference and analysis of QoE in mobile contexts, as well as for implementing user profiling based on successful-QoE experiences.**

***Index Terms*—quality of experience; context-aware; QoE modeling; interaction modeling; user profiling.**

I. INTRODUCTION

Quality of Experience (QoE) is a subjective measure of users' experiences with a service. It focuses on those aspects that users directly perceive as quality parameters, and that finally decide the acceptability of a service. QoE is not just related to Quality of Service (QoS), but it is a broader construct beyond technical and objective system performance metrics [1], [2], [3], [4]. It encompasses users' behavioural, cognitive, and psychological states along with the context in which the services are provided to them. This is particularly true in mobile contexts, where applications are dynamically used in different scenarios and social contexts [4].

Moreover, context-aware systems extract, interpret, and use context information to adapt their functionality to the current context of use [5]. By "context" we mean any information used to characterize the situation of an entity, e.g., person, place, or object, and that is considered relevant for the user-system interaction analysis. Hong et al. [6] differentiate among external context, which involves data referring to the physical environment, e.g., location, sound, time of the day, etc., and internal context, which involves data related to the cognitive domains of the user, e.g., emotional state.

Complexity of interaction within mobile scenarios has increased dramatically in the last few years. Users and their handheld devices are continuously moving in several simultaneous fuzzy contexts [6]. This dynamic environment sets special requirements for mobile applications' usability and the acceptance of such systems. A close relationship between interaction, its context, and QoE can be found in these environments. However, the lack of a uniform approach for modeling the information related to interaction within a specific context is obvious [7]. This is why this work proposes incorporating user ratings and context-aware information into user-system interaction analysis methods, providing a uniform basis to quantify interaction within mobile scenarios, and use it to determine QoE.

However, incorporating these data into user-system interaction analysis processes poses several problems. One of them is deciding what parameters are useful to capture QoE in mobile contexts [4]. We consider essential that such parameters have to be collected, as far as possible, by using current devices' capabilities. The low standardization of technologies used in context-aware systems is also a problem [6]. A common representation of the context of applications is needed to support standard analysis and decision processes, as well as to support cooperation between different QoE analysis applications. A related problem is how to build "standard" user-interaction profiles, which are used by applications or systems to adapt themselves to provide a better QoE.

According to these problems, the following research questions are posed:

Q1: How can rating and context information be properly incorporated into interaction analysis processes?

Q2: How can QoE of different users be compared to each other, as well as QoE inferred from different systems and/or contexts?

Q3: Is it possible to build a user's interaction profile based on successful-QoE experiences?

To answer these questions, this paper briefly describes the design of a meta-model arranging dynamic interaction parameters. This meta-model is augmented with parameters describing users' perception of interaction quality, as well as context information. It provides a uniform representation of user-system interaction within real mobile contexts. Instances of this meta-model provide a basis to determine and compare QoE of users in such contexts, as well as to make decisions at run-time to provide a better users' experience.

The rest of the document is structured as follows. Section II

 ISBN: 978-1-61208-232-5

describes an overview of the meta-model design mentioned above. Section III describes some considerations about the implementation and the applications of the meta-model in current mobile scenarios. Finally, Section IV includes some conclusion and future lines of work.

II. QoE-AWARE INTERACTION ANALYSIS

The approach described in this paper tries to give an answer to the three research questions posed above. First, to answer research question Q1, the design of a meta-model including interaction, user-rating and context data is proposed. It structures all these data to be the basis for the implementation of QoE analysis and inference processes. We propose to base this meta-model design on an existing one [8], [9] which is being developed in parallel to this work, in a joint effort between the Cátedra SAES [10] and the Telekom Innovation Laboratories [11] to quantify interaction in multimodal contexts.

The base meta-model describes interaction by turn, i.e., each time the user or the system take part in the dialog, following a dialog structure, i.e., a set of ordered system- and user-turns. This "step by step" description of interaction creates a relationship between data and time, providing new opportunities for the dynamic analysis of interaction. This meta-model handles different modalities at the same level using common metrics to describe interaction. These metrics are structured within a common representation, allowing the comparison among different interaction records. Collected data (turn content, meta-communication, I/O information, and modality description) are partly based on the well validated parameters and concepts described in [12], [13].

Since the base meta-model only quantifies user-system multimodal interaction, it was extended in to ways. On one hand, user-rating parameters as the used in questionnaires like AttrakDiff [14] were added to measure how attractive and user-friendly is the product under test. On the other hand, the model was extended with new parameters to describe the interaction context in mobile scenarios. Thus, the model not only provides a link between interaction data and time, but new links between interaction and, for example, user's opinions, information about location, social context, device features, etc. are created. Figure 1 depicts the kind of parameters considered by the proposed design.

Human-computer interaction parameters —included in the base meta-model— are used to quantify the interaction of the user with the system, e.g., quantity of information provided by the system, average reaction time of the user. *User rating* parameters are used to measure the experience of users with the system under test, e.g., motivating, human, clearly structured. They measure how attractive the system/application is in terms of usability and appearance. The validity of questionnaires like AttrakDiff as a method to extract users' experience is shown in related work, e.g., [15].

Communication parameters describe the features of device connectivity, e.g., if the user is on-line or not, connection bandwidth. *Location and time* parameters describe the position of the user while interacting the system, as well as a time reference, e.g., the user is moving, it is Friday night. *User* parameters describe peculiarities of the person using the application and the device, e.g., gender, age, disabilities. *Social context* parameters are those that can be extracted from social media, and are interesting for the interaction analysis, e.g., if the user is along with their friends, if he/she is within an office context. Finally, *Device* parameters describe the peculiarities of the device being used, e.g., screen size, input and output methods.

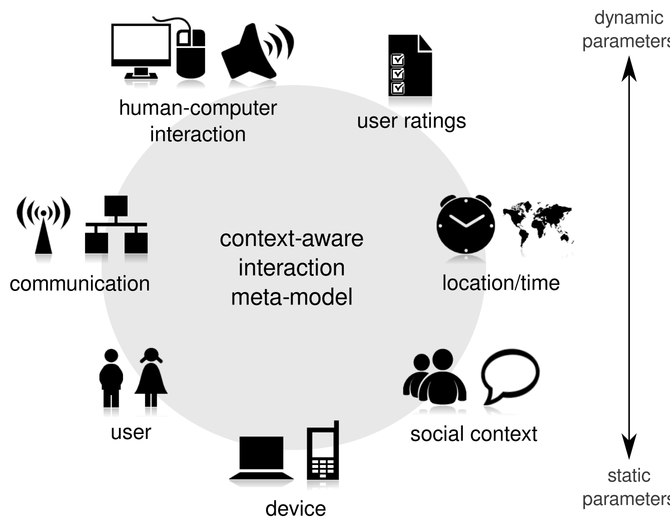

Figure 1. Design overview of the proposed meta-model.

Some of these parameters are run-time and have to be collected many times during interaction, e.g., quantity of user input at a specific time. Others are not, and are collected only once, e.g., screen resolution. This feature is specially relevant to know where the parameters are included in the model design. Run-time ones are included at turn-level, while static ones are included at dialog level.

Instances of this meta-model describe user-system interaction within its mobile context, and are ready to support further analysis, comparison, transformation, and decision processes. The great majority of the parameters described above are intended to be collected automatically, e.g., by using tools like the Android HCI Extractor [16] which extracts multimodal interaction data at run-time. However, those based on subjective judgments of the user or the expert have to be manually annotated in most of cases. Anyway, automatically collected or not, the same metrics —structured into a common representation— are used to quantify the interaction between the user and the system. This provides experts and tools with unified criteria to describe the interaction process. Different interaction records can be analyzed and compared regardless of the system/application under testing, the interaction context, even the modalities used to provide input and output data. This answers research question Q2.

To answer question Q3, the reader can consider an instance of the meta-model described above as a three-dimensional representation of an interaction "occurrence". These dimensions

 ISBN: 978-1-61208-232-5

are the user who is performing the interaction ($u \in U$, U the set of all users under study), the application or system with which the user interacts ($a \in A$, A the set of all applications or systems under study), and the context in which the interaction process is performed ($c \in C$, C the set of all the possible contexts under study.) Let I be a set of instances of the model described above, each instance $i_n \in I$ represents one of the interaction occurrences in the space (u_i, a_i, c_i). If we consider all the instances i_n in the space (u_i), i.e., all the interaction occurrences of the user u_i, these can be used to build a "user interaction profile" representing the features of the behavior of this specific user.

Maybe using only one dimension to analyze interaction is not useful to make decisions. However, if for example the interaction occurrences in the space (u_i, a_i) are used to build a profile, we can analyze the behavior and ratings of a user using the same application in different contexts. Thus, the application can be adapted to the current context, as mentioned in [4]. Using the occurrences in the space (u_i, c_i) allow us to analyze how the user behaves in a specific context, and those in the space (a_i, c_i) are valid to analyze how different users interact with an application in a specific context. The process gets more complex if sub-dimensions of these three dimensions are considered, but this is not the goal of this paper. This shows that instances of the proposed meta-model are valid to create different interaction profiles not only related to users, but also related to the system/application in use or the interaction context.

Finally, we consider essential the easy incorporation of the proposed solution into current mobile devices, i.e., tablets, smartphones, etc. From a practical point of view, developed solutions should be easily built into the kind of devices used nowadays. This not only fosters using such a kind of testing tools into current applications and systems, but it will ease the full implementation of context- and QoE-aware methods in real life, and not only for laboratory environments [6]. This is why we argue for using current devices capabilities to collect interaction and context data, e.g., the windowing system to collect touch interaction metrics, internet-based applications to get social information, device's sensors as GPS to get position. Even users' perception of interaction quality when possible, e.g., encouraging the user to rate interaction at run-time. Therefore, advanced sensors are not required to fill the model instances.

III. Meta-Model Implementation and Applications

Our implementation of the base meta-model will use the facilities offered by the Eclipse Modeling Framework (EMF). The widely used EMF allows the definition of comprehensible, flexible and extensible meta-models, as well as the syntactically validation of concrete model instances. Tools like EMF help to make the modeling process more effective, and provide indispensable functionality to validate and extend the meta-model [17]. EMF provides model transformation and automatic code generation functionality as well. The design of the meta-model will be used to automatically generate the source code, which has to be integrated into the applications in which new model instances will be created.

To collect interaction and context parameters automatically, it is proposed using a tool based on the Android HCI Extractor. [16] This open-source tool can be extended to collect, as far as the device allows, all the interaction and context data necessary to fill model instances. User ratings might be automatically collected as well, e.g., by showing questionnaires after test trials. This tool will be used to create model instances at run-time. Such instances are valid to represent many different interaction scenarios, from the usage of an application during some minutes, to the usage of a device during hours. Despite the architecture and behavior of the HCI Extractor can be ported to other mobile systems —it uses a reduced EMF Java implementation that can run in many platforms— currently only Android is supported. However, Android can run in many different mobile platforms, e.g., smartphones, tablets, netbooks, smart-tv, etc.

Once created, the instances provide a basis on which to implement different analysis and evaluation processes. QoE inference is the first result that comes to mind. The data included into a model instance can be used to systematically determine the QoE of a user within a mobile context. Interaction data can be fused with context information and users/experts ratings to determine QoE, e.g., by using Bayesian networks as in [4] Moreover, thanks to the run-time nature of the meta-model, QoE can be estimated in real-time. In case the resulting value is not the expected, the interaction history and the context can be analyzed for a specific interval of time to make a decision that makes QoE to improve, e.g., by adjusting microphone settings, changing screen brightness.

As a common representation is used, different instances can be easily compared to each other, e.g., to detect why QoE worsens when using an application in a different scenario, to know why an application provides a better QoE than another. Finally, model transformation processes can be implemented using the high expressiveness of EMF-based tools, e.g., ATL [18]. Original model instances can be transformed into instances of other meta-models, which provide different perspectives of the data collected during the interaction process, e.g., a summary meta-model linking only context and ratings data, a statistical meta-model aggregating users ratings. Thus, model transformation is valid to build user interaction profiles as well. Let *Model_B* be a meta-model describing the user interaction profile. Several instances of the meta-model proposed in this paper (say *Model_A*) can be used to build an instance of the new model by simply using ATL transformation rules. The process is completely automatic, as data in *Model_A* instances are used by ATL to fill data fields in the *Model_B* instance according to the rules.

Some validations tests were conducted in the context of the PALADIN project [8], [9]. The participants used multimodal input (speech + touch) to book a restaurant within an Android smartphone. These tests where used to show the validity of the interaction meta-model on which the proposed solution is based. Similar tests can be conducted to show the validity of the solution proposed in this work, but now using a context-dependant application and collecting real or simulated context data. Then, the model instances will be used to determine QoE of each participant using different modalities or a combination of them.

IV. Conclusions and Future Work

The design of a meta-model including data about user-system interaction and its context is described. Most of the parameters included in this design are collected using current devices' capabilities; subjective ones have to be annotated manually. This meta-model provides a common representation of interaction, allowing the inference, analysis and comparison of QoE in mobile contexts. A relationship between user-system interaction, its context, and users' perception of quality is created. Moreover, a strong relationship between these data and time is provided as well, opening up new opportunities for the dynamic analysis of QoE. Its dynamic nature also allows to make QoE-aware decisions at run-time. Instances of this meta-model are also valid to create user interaction profiles based on successful-QoE experiences.

This approach poses lots of challenges with which to deal until reaching its final implementation. One of them is treating the variety, diversity and big amount of interaction and context data. This solution is not aimed at modeling "the entire world", but only data that is relevant for the analysis of QoE have to be considered. A well balanced set of parameters has to be chosen for the model design. This set should be as small as possible, but enough to determine QoE in mobile contexts.

Choosing an adequate abstraction level for the parameters is also very important, e.g., the user is in a specific geographic coordinate vs. the user is in the office. Dealing with cognitive data automatically is also challenging. Emotional state of the user and cognitive elements have to be incorporated into the meta-model, as well as users' quality perception and experts' verdicts. Users' security and privacy problem should be also posed and discussed.

Acknowledgement

This paper has been partially funded by the Cátedra SAES of the University of Murcia initiative, a joint effort between SAES [19] and the University of Murcia [20] to work on open-source software, and real-time and critical information systems.

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