A Content-Adaptation System For Personalized M-Learning

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Abstract— **Evolution of mobile technologies and widespread adoption of mobile devices in learning today is momentous. Mobile learning refers to the use of portable devices to study independent of location and time. To allow flexible learning to occur, content adaptation is necessary. Content-adaptation aims at delivering the most suitable learning elements in dynamic conditions using different contextual information from various sources in order to enhance the learners' experiences. This paper describes our ongoing research project, the context-aware mobile learning application, Mobiware that makes use of contextual data in mobile learning for content-adaptation. Important information was gathered from individual learners, the device used and the surrounding to give rise to independent customized learning materials. The aim of developing this mobile application is to set a dynamic system, which instantly acknowledges different user situations, and deliver the best-adapted learning content to the learner. Details about the current trends in mobile learning are reported which leads to the proposed context-aware mobile learning application.**

Keywords—mobile-learning; content-adaptation; personalization; adaptation strategies; context-awareness

I. Introduction

Mobile learning allows learning to take place anytime and anywhere with the aid of handheld devices. The infinite multiplication of different mobile technologies that are available at present makes content adaptation an important issue to focus on. Besides, learning conditions are further expanded across numerous contexts. Portable devices are moving towards generating and presenting more personalized context-driven learning elements matching to the learners' interests. A number of recent works did consider the adaptation of contents on mobile devices [1-2]; however, they did not exploit the full capabilities that recent mobile devices provide [3]. The objective is to focus on interactive learning while allowing maximum flexibility under multiple learning conditions [4]. In this way, learners benefit from a highly motivated and responsive learning while putting forward their own learning strategies. Consequently, it enhances their learning trends and experiences [5-6].

To improve this learning approach further, personalized learning is important. This learning condition implies that the learner can customize the learning contents based on his/her needs and requirements including the contextual information received from other sources. These sources regroup both the internal or intrinsic and external or extrinsic contexts [7-8] or most commonly identified as physical and logical context [9]. Physical context refers to context defined by hardware sensors such as light, sound, touch, temperature and many others. Logical context specifies user interactions, such as the learner's goals, tasks to complete and emotional state. Context is any information used to describe the situation of an entity [7]. The foremost characteristics that define and make context useful are our location, the presence of people and the existing resources in the surroundings. Contextual data are further grouped into four distinct categories which are described below [12-13, 16].

- Identity: a unique identifier for the entity.
- Location: includes spatial and geographical data.
- Physical: contains properties distinguished by the user. It includes noise level, touch, temperature, light intensity and many others.
- Time: Time of the day, month, year, date.

The above mentioned four context categories funnel the primary ones. External context is the most valued among the categories. Many recent mobile learning applications made use and explored at maximum this context type. However, some efforts to use internal context information were also seen

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[10-12]. Context can be based on different states such as the learner's educational, activity, infrastructure and surrounding state [13-14]. The learner's state is a major factor to consider in the internal context. It consists of the cognitive skills, intentions, learning styles, preferences and interactions with the system [15]. Contextual information changes at swift occurrences over time and provides new definitions using real life settings to learn using mobile devices in different contexts [16-17]. Mobiware aims at facilitating personalized learning through the above stated features. The system adapts itself to the diverse learner's requirements. Therefore, instant alteration and reasoning of the application are based on the captured data from varied attributes.

II. Content-adaptation in Mobile Learning

Content-adaptation is to date one of the most valued factors in mobile learning and will certainly be taking the lead to deliver acute instructed learning contents making use of heterogeneous devices. Content-adaptation aims at presenting the most appropriate learning elements to the learner under different contexts. Besides, an adaptive system is one that adapts itself to the different needs or circumstances while considering the various properties of the mobile system [18]. Content-adaptation can be regrouped under two types, static and dynamic adaptation. Static adaptation filters and delivers content elements from the database when a request from the learner is notified whereas in dynamic adaptation contents are adapted in real-time [19]. Static adaptation remains the most labor-intensive approach in adaptation for example various layouts of the same web page have to be provided to fit the varied screens of the mobile devices. Reviews from researchers supported the fact that monitoring the learning process of the student under different contexts still remains a challenging issue [20]. Dynamic content adaptation can be further categorized under four different levels as illustrated in the following diagram.

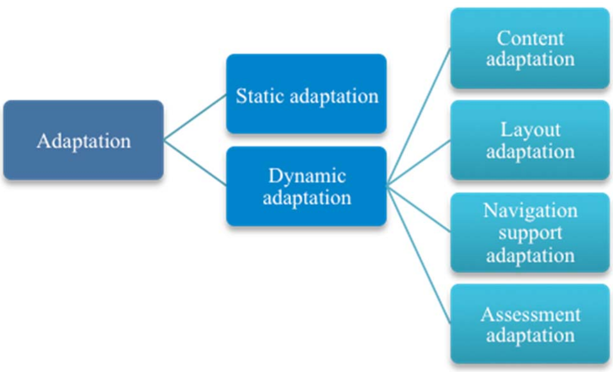

Fig. 1. Structure of content-adaptation

Content-adaptation allows suitable learning objects to be selected according to the learner's preferences such as his learning style, his learning priorities, his knowledge level and contextual features such as the level of concentration, the cognitive load of the learner, the situating environment and the time during which learning occurs.

Good design is important to present content based on both the student's previous competencies and preferences. Besides, learning under appropriate design using striking colors, readable fonts, images and videos in suitable formats through heterogeneous devices motivates the learner to study more efficiently [21 - 22].

Navigation support adapts itself according to the device features such as its multiple screen sizes, different interface presentation, and the contextual information that the device makes use of [23]. The media types (textual, pictorial, video or audio format) through which the information is presented will directly influence the graphical characteristics of the mobile device.

The learning elements allocated for self-assessment are adapted based on the needs of the individual learner [24]. Using the assignment adaptation, the cognitive level of the learner is assessed and appropriate content types are delivered based on that information. The cognitive theory defines appropriate learning under the lowest cognitive load and vice-versa [25].

To set a dynamic context-aware adapted system, the mechanism has to match to the contextual information at different levels on the running platform. The initial and immediate contexts that the system requires are the computing contexts such as the device characteristics, network and bandwidth conditions and the physical contexts categorizing location, activities of the learner and time. Dynamic capabilities regarding the internal changes such as his mood, behavior, likes and preferences of the learner are important factors that should not be disregarded. The goal of the proposed system, Mobiware, is to respond to a set of dynamic instances instead of static, to be compatible through all the heterogeneous devices and to shape an independent and reusable learning platform.

III. Design of The Context-Aware Mobile Learning System

The proposed system introduces a customized learning application independent of the environment of the user and the time. The mobile learning application captures both internal and external contextual information. It adapts itself based on the characteristics of the handheld device, the actual environment of the user and the requirements or needs of the learners. This responds and resolves to an instantaneous or dynamic learning process where the learner can effortlessly exploit maximum content-wise and acquire the best learning experiences. Features of Mobiware begin with the identification of the learner. The individual is prompted with queries about personal details such as his/her name, age, email address and preferences/likes about the topic. These information provide an overview of the learner's choices and helps to identify and construct individual learner's profiles which the mobile application makes use to deliver accurate customized learning contents. Moreover, situational context information based on the current enclosure of the learner is also saved in the application which is accounted for adapted learning elements. This section showcases the architecture and design principles adopted for the system. A reliable set of parameters were defined and layered based on the multiple contextual information obtained from the device, the surrounding environment and the user.

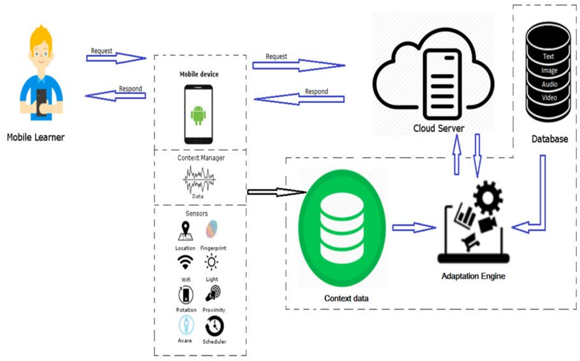

Fig. 2. Architecture of the Learning mobile application

To achieve interoperability in the content-adaptation system using personalized learning, Mobiware contains data attributed to the diverse pre-defined contextual conditions. As the learner logs in the system, it identifies a returning user and prompts a new learner to register in the system. Once registered, the user fills in data about his/her preferences and personal details which eventually helps to build individual profiles. Initially, the learner makes a request for a particular topic. The context manager captures, monitors, crosschecks against the learner's profiles and filters appropriate contextual information from the surrounding and the application data with the aid of sensors which works permanently in parallel. This filtered data is then stored in the context data storage unit where it is further processed in the adaptation engine. The resulting data from the adaptation engine is used to process the learning elements and to generate content types that are most appropriate for the current contexts. Based on the requirements of the learner and limitations of disk space in the system, some contents may then be stored in the cloud setting.

Adaptation in the Mobiware application concentrated on two main sections. These are the physical context adaptation and the user context adaptation. The flowchart below illustrates the flow levels of adaptations based on the physical conditions.

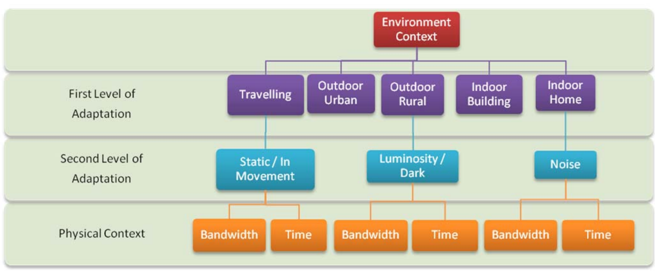

Fig. 3. Flow of the different levels of adaptations (Physical Contexts)

A. First Level of Adaptation (Environment)

Adaptation in the first level determines the geographical position of the learner. Indicated as in figure 3 above, the Outdoor urban environment regroups all crowded and loud places, examples may include in the university yard during lunchtime or shopping in a crowded environment. The Outdoor rural scatters places where it is not much crowded. The Indoor building can include a classroom during a learning session and indoor home simply defines the student's house, which is said most of the time is to be a cozy and quiet place.

B. Second Level of Adaptation (The environmental conditions)

This adaptation level starts with considering the motion of the learner. Actions such as the acceleration, rotation, tilting are determined. It then checks how light can affect the surrounding during the learning process. Reading under dim light can disrupt the learning pattern and halt the process. Therefore it is important to consider the regenerations of learning contents under this condition. Lastly, the surrounding noise level is another factor that the application has investigated in order to generate accurate content types. The system is able to detect the connection of an ear piece and delivers appropriate audios or videos together with the learning materials. Once these pieces of information are filtered out, they are merged with the initial level of adaptation. Hence, this combined information further enriches the delivery for a most precise and impactful adaptation of learning contents to the learner.

Physical contexts such as the time and network capabilities are used to advance the effort to produce dynamic and self-adapted, customized learning materials to the learner. Besides, the internal contexts such as the user's profile (preferences, likes, age) with cognitive load conditions including the learner's learning style, attentiveness, learning intentions are captured. The following section defines the set of contexts that have been considered for performing content adaptation in Mobiware.

C. Physical Context - Time

Properties distinguishable based on the actual time of the day defined the appropriate content types for the learner. If the learner has logged in the morning, contents will load with maximum details with utmost complexity in the lessons to help in maximizing the user's knowledge level. This is because, during this time the concentration level of the learner is said to be at its peak. The time property was split into four categories (morning, day, afternoon and night).

D. Physical Context – Network capabilities(Bandwidth)

The rapid alteration of the bandwidth over time and space made it a necessity to capture throughout its fluctuations and deliver contents accordingly. For example, with a low bandwidth, high definition (HD) videos were restricted from streaming. Instead, they were made available in their lower stream format possible. As the bandwidth grows, a myriad of content types were auto-selected to merge the existing array of content types forming a new selection of elements based on the different contexts information obtainable. In addition to the environment context used to adjust the learning elements based on the immediate situations, internal context data are also taken into account. The next section concentrates mainly on the user context adaptation in the system.

E. *User Context – Preferences/Likes*

The learner is prompted with a quick survey during the registration process. In this way, the student's preferences are captured. These information together with the prior knowledge of the individual are recorded in the database for further use to deliver customized data during learning sessions.

F. *Cognitive Context – Learning Style*

The comprehension of the learner is assessed through regular quizzes and the subsequent contents/lessons are adapted in order to better fit the learner. For example a slow learner will be given more examples in order to increase the comprehension of the learner. The comprehension level of the learner are classified into 5 categories are shown in the table below. The proposed adaptions for each comprehension category are also given.

TABLE I. LEARNING FLOW ADAPTATION OF THE CONTENTS

Learning Flow Adaptation	
% level of good answers	***New adaptation of learning elements***
80-100%	Proceed while increasing the learning contents with fewer details. A fast learner requires less information to understand.
60-80%	Continue with the normal flow of learning contents
40-60%	Restructure learning contents with more content types (audio, videos, images)
20-40%	Restructure of learning contents with even more content types and learner is given optional examples to consult in order improves comprehension.
0-20%	Restructure learning contents with a maximum number of content types and provide all possible examples to reach a suitable comprehension level

The normal learning flow continues as long as the learner is able to answer to the questions set at the end of each study sessions. If the learner scored all five questions correctly, he/she can proceed with the learning sessions with fewer details. As the score reduces, the learning contents get restructured based on that result with more comprehensible facts to enhance the learning conditions. The least scenario is when a learner scored a range of 0-20%, he/she is then presented with learning contents with a combined set of content types and with several examples. This includes animations, summaries of lessons, images representing simple theories and captions.

G. *Cognitive Context – Attentiveness*

The attentiveness of the learner defines how much time the learner is ready to allocate during the learning process. Moreover, logging the time taken for reading is considered as a requirement to find out how attentive the user is.

H. *Cognitive Context – Learning Intentions*

The learners' intentions can be found through his/her interactions in the system. If a maximum number of inputs are detainable towards a defined lesson, this result could presume that the learner is much interested in that particular topic.

IV. IMPLEMENTATION OF CONTENT ADAPTATION MECHANISM FOR MOBILE LEARNING

In this section, we define the implementation process used for Mobiware. Parameters from the initial level of adaptation process defined in section III are declared as global variables in the early development. This level of adaptation made use of an activity variable which determined the current location of the learner. An Activity Recognition API is used to capture and analyze the movement of the learner.

Bandwidth and time are the other parameters considered. The current time was monitored based on four levels of adaptations which are morning, afternoon, evening and night. In this way, switch cases responds on the value that is filtered to the application. Obtained values from the variables are stored in the database and are merged with the second level of adaptation data to produce a more dynamic response. Data are updated using a thread at three seconds interval. Thus, data received from the application always stays on a refreshed state to deliver in-time and adapt the learning materials as per the user's requirements and needs.

```
String mLastUpdateTime =
DateFormat.getTimeInstance().format(new Date());
String hour =
Character.toString(mLastUpdateTime.charAt(0))+Character.toString(
mLastUpdateTime.charAt(1));

if (Integer.parseInt(hour) >= 03 && Integer.parseInt(hour) <= 10){
        MainActivity.tim = "morning";
}elseif(Integer.parseInt(hour) >= 11 && Integer.parseInt(hour) <=
15){
        MainActivity.tim = "afternoon";
}elseif(Integer.parseInt(hour) >= 16 && Integer.parseInt(hour) <=
20){
        MainActivity.tim = "evening";
} elseif(Integer.parseInt(hour) >= 21 && Integer.parseInt(hour) <=
23){
        MainActivity.tim = "night";
}
```

Fig. 4. The time adaptation function with inbuilt thread.

Four types of bandwidth connections are defined to test for the network capabilities. These include low, medium, good and high. Based on the receiving context data, if the bandwidth is seen to be moderate and matches the defined value from the WifiManager, the assigned bandwidth looks proper for fluid learning and as it increases, the system allocates higher network priority to the content elements. The same conditions apply for the low and medium bandwidths.

The noise level is captured using the microphone in the device with the function getAmplitude. The media recorder obtains the values in decibel and is stored in the database. Moreover, the headset state method helps in detecting the presence of a plugged earpiece.

```
public void updateTv (){
        handleHeadState(this);
                if(getAmplitude() > 20000){
                        mStatusView.setText("High");
                        MainActivity.Noisee = "High";
                }else{
                        mStatusView.setText("Low");
                        MainActivity.Noisee = "Low";
                }
}

public int getAmplitude(){
        If (mRecorder != null){
                return (mRecorder.getAmplitude());
        else
                return 0;
}
```

Fig. 5. Noise level adaptation function

Quiz questions are made available at regular intervals during the learning sessions for learners to self-assess their learning progressions. A total of five simple questions are set based on the selected subject. The score helps in re-adjusting the learning elements in the application using the Learning Flow Adaptation. A low score will reorganize the contents in simpler and effective ways using combined set of content types and additional examples in order to improve comprehension. This may include animation or pictures with clear captions illustrating complex terms. A higher score will allow the student to proceed with even less details or in the normal learning trend that the learner adopted initially.

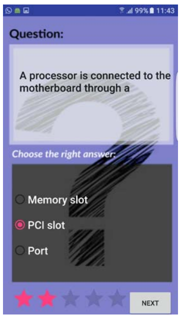

Fig. 6. Quizzes examples set for a particular learning topics

V. RESULTS & DISCUSSIONS

Different scenarios were tested which responded dynamically under the classified set of rules defined in sections III and IV. The test cases were categorized into two principal groups namely the Atomic Parameters and Composite Parameters. Atomic Parameters responds to only a single unit parameter at a time while Composite parameters merge various parameters to demonstrate how adaptation based on the combined contextual information received at different levels delivered the most accurate learning elements to the learner.

A. Atomic Parameters Test Case:

The different contextual parameters have been tested one at a time in the Atomic test cases. The following table shows the distinct performance of the parameters used on an individual basis for dynamic content adaptation of learning elements.

TABLE II. ATOMIC PARAMETERS TEST CASE FOR ADAPTATION

Parameters Monitored	***Interpretation of Parameter***	***Parameter Classification***	***System Adaptation***
Travelling	getConfidence function is used to detect the movement of the user – Activity Recognition API.	Captures movement and uses the google geolocation API to detect the current location of the user.	Responds to the nearby spot in which the user is currently in.
O. Urban	Extracts the bandwidth ID, checks for the current location based on the Google Map API, responds to any earpiece connected and detects the noise level and light intensity in the current setting.	Noise level, light intensity, bandwidth, activity	Contents are dependent on the varied intensities of noise and light, the bandwidth that the device captures and the current activity of the learner (either idle or in movement).
O. Rural	Extracts the bandwidth ID, checks for the current location based on the Google Map API, responds to any earpiece connected and detects the noise level and light intensity in the current setting.	Noise level, light intensity, activity, bandwidth	Contents are dependent on the varied intensities of noise and light, the bandwidth that the device captures and the current activity of the learner (either idle or in movement).
Indoor Building	Extracts the bandwidth ID, checks for the current location based on the Google Map API, responds to any earpiece connected and detects the noise level and light intensity in the current setting.	Noise level, light intensity, bandwidth, activity	Contents are dependent on the varied intensities of noise and light, the bandwidth that the device captures and the current activity of the learner (either idle or in movement).
Indoor Home	Extracts the bandwidth ID, checks for the current location based on the Google Map API, responds to any earpiece connected and	Noise level, light intensity, bandwidth, activity	The application captures the current location of the learner based on the Google Map API with the connecting bandwidth ID,

Parameters Monitored	*Interpretation of Parameter*	*Parameter Classification*	*System Adaptation*
	detects the noise level and light intensity in the current setting.		being saved as home.
Static/In movement	getConfidence function used to detect the value of the user	Captures movement (rotation, tilting, acceleration etc)	Responds to nearly the correct movement the user undergoes
Luminosity / Dark	Dependable on the environment we are in – Fluctuations possible	Light intensity	Responds correctly to the thread set
Noise	Fluctuate as per surrounding	Noise level	If any earpiece is plugged in, the device receives a notification.
Bandwidth	Fluctuate as per surrounding	Nearby network capabilities	Learning elements are adjusted based on the fluctuations values obtained
Time	Measures the current time of the day or night	Morning, Day, Afternoon, Evening	Contents delivered responds to the right time obtained

Independent context parameters were observed and used in the application to perform adaptation in the system first, followed with the grouping of each of the above into composite parameters in the next level. Each of the defined parameters contributed effectively to the pre-estimated results.

B. Composite ParametersTest Case:

The composite parameters test case evaluates the combination of the differing variables obtained while being in varied environment. The table has been split in levels, which illustrate the flow of the conditions per obtained parameters, and how adaptation occurs in the application. The bold characters in the table represent the units used during the test intervention.

TABLE III. COMPOSITE PARAMETERS TEST CASE

Parameters Monitored	*Interpretation of Parameter*	*System Adaptation*
Travelling + Static or In movement + Bandwidth + Time	Application returns travelling as the first level of adaptation combined with motion parameters. It proceeds further to determine the actual bandwidth and time.	System is adapted as per the interpretation of the current parameters obtained. It adapts itself based on the fluctuations of the delivered results.
Travelling + Static or In movement + **Luminosity or Dark** + Bandwidth + Time	The travelling parameter further adapts with the motion in the second level including luminosity environment.	Contents delivered responds based on the composite parameters that the application obtains in the situating environment.
Travelling + Static or In movement + Luminosity or Dark + **Noise** + Bandwidth + Time	The noise parameter is included in the hierarchy of parameters defined. The varied noise level adds another interest in adaptation in the learning contents to be deployed.	The fluctuating level of noise and the presence of any ear piece re-construct the data in the learning contents differently as it adapts itself.
O. Urban + Static or In movement + Bandwidth + Time	If O. Urban is the resultant of context aware parameters, the system gets adapted to this context category.	Being in an O. Urban environment, the contents get adapted with the most subtle content types such as more images to merge the situation.
O. Urban + Static or In movement + **Luminosity or dark** + Bandwidth + Time	Luminosity and darkness are included in the fusion to uphold the delivery of context-wise educational contexts.	Contents are delivered with the finest content types based on the light levels and O.Urban conditions.
O. Urban + Static or In movement + Luminosity or dark + **Noise** + Bandwidth + Time	The presence of noise in the surrounding takes up the whole compound of O.Urban to deliver an appropriate context-aware learning content.	The detection of an ear piece results in the sound level increase and vice-versa.
O. Rural + Static or In movement + Bandwidth + Time	The conditions of an O.Rural environment bring forward a different adaptation process in the contents delivered in the system.	Learning contents are adapted with more detailed elements (texts) rather than simplistic contents delivered.
O. Rural + Static or In movement + **Luminosity or dark** + Bandwidth + Time	Parameters get further adapted with the luminous or dark environment.	Contents adapt themselves based on the light intensity in the environment.
O. Rural + Static or In movement + Luminosity or dark + **Noise** + Bandwidth + Time	Checks for any noise in the surrounding and adapts its content based on the results the application returns.	The noise level is checked and defines the most appropriate learning contents to the learner.
Indoor Building + Static or In movement + Bandwidth + Time	Conditions met for indoor building provide learning contents initially with a combination of the fluctuating bandwidth and the actual time of the day.	This parameter presents calm and good learning environment where contents are adapted much wisely with possibilities of different content types available for learning.
Indoor Building + Static or In movement + **Luminosity or dark** + Bandwidth + Time	The learning contents in the system get refracted based on the conditions of the light levels.	The light intensity causes a fluctuation in the adaptation process mixed up with the indoor setting parameter as it increases and decreases.

Parameters Monitored	*Interpretation of Parameter*	*System Adaptation*
Indoor Building + Static or In movement + Luminosity or dark + **Noise** + Bandwidth + Time	Detection of noise in the indoor building, adapts the contents based on the actual noise level.	Fluctuations in contents are predicted as the noise levels keep on changing.
Indoor Home + Static or In movement + Bandwidth + Time	At home the content elements are delivered in its most elementary conditions with a good flow of several adaptation conditions	Options are given to the learner as to how he/she wants the contents to appear on screen since at home the atmosphere is mostly quiet and better to learn.
Indoor Home + Static or In movement + **Luminosity or dark** + Bandwidth + Time	Adaptation of contents is dependent on the light intensity to provide an effective learning condition.	Learning under dim or bright light adapts the contents in the mobile device based on the light intensity.
Indoor Home + Static or In movement + Luminosity or dark + **Noise** + Bandwidth + Time	Application detects the noise levels at home and produces the best-suited learning elements to the learner.	The home atmosphere remains a quiet place which does not require exhaustive adaptation for noise. However, if noise level is high, then content gets adapted as per the situation.

Methods used to perform adaptation on the parameters were as expected. Response was so far positive on the different contexts used.

TABLE IV. ACCURACY TEST FOR THE CONTEXT-AWARE PARAMETERS

The below accuracy test case provides an overview on the state of the adaptation level in the application.

Parameters Monitored	*Description*	*% Accuracy*
O. Urban + Static or In movement + **Luminosity or dark** + Bandwidth + Time	Out of 10 trials carried out, 7 good response were obtained for the opted parameters	70%
Travelling + Static or In movement + **Luminosity or Dark** + Bandwidth + Time	Out of 10 trials carried out, 8 good response were obtained for the opted parameters	80%
Travelling + Static or In movement + Luminosity or Dark + **Noise** + Bandwidth + Time	Out of 10 trials carried out, 8 good response were obtained for the opted parameters	80%
O. Urban + Static or In movement + Bandwidth + Time	Out of 10 trials carried out, 7 good response were obtained for the opted parameters	70%
O. Urban + Static or In movement + **Luminosity or dark** + Bandwidth + Time	Out of 10 trials carried out, 9 good response were obtained for the opted parameters	90%
O. Urban + Static or In movement + Luminosity or dark + **Noise** + Bandwidth + Time	Out of 10 trials carried out, 8 good response were obtained for the opted parameters	80%
O. Rural + Static or In movement + Bandwidth + Time	Out of 10 trials carried out, 6 good response were obtained for the opted parameters	60%
O. Rural + Static or In movement + **Luminosity or dark** + Bandwidth + Time	Out of 10 trials carried out, 7 good response were obtained for the opted parameters	70%
O. Rural + Static or In movement + Luminosity or dark + **Noise** + Bandwidth + Time	Out of 10 trials carried out, 8 good response were obtained for the opted parameters	80%
Indoor Building + Static or In movement + Bandwidth + Time	Out of 10 trials carried out, 6 good response were obtained for the opted parameters	60%
Indoor Building + Static or In movement + **Luminosity or dark** + Bandwidth + Time	Out of 10 trials carried out, 7 good response were obtained for the opted parameters	70%
Indoor Building + Static or In movement + Luminosity or dark + **Noise** + Bandwidth + Time	Out of 10 trials carried out, 7 good response were obtained for the opted parameters	70%
Indoor Home + Static or In movement + Bandwidth + Time	Out of 10 trials carried out, 8 good response were obtained for the opted parameters	80%
Indoor Home + Static or In movement + **Luminosity or dark** + Bandwidth + Time	Out of 10 trials carried out, 7 good response were obtained for the opted parameters	70%
Indoor Home + Static or In movement + Luminosity or dark + **Noise** + Bandwidth + Time	Out of 10 trials carried out, 7 good response were obtained for the opted parameters	70%

The average result range in the above table is beyond 50% but less than 95%. Further research needs to be carried out so as to improve detection accuracy of the proposed system (from 70% to above 95%) for more reliable adaptation in context.

C. User Context Test Case:

The application allows the possibility for a learner to assess his/her own knowledge level during each course. The next test case shows how the learning elements for Learner with ID 1 are adapted during the learning sessions using Mobiware. The scenarios hold different situations in which the learner experiments his/her progression based on the cognitive load for the allocated time set.

TABLE V. COGNITIVE LOAD TEST CASE FOR USER ADAPTATION

User ID	Cognitive Level Test Case		
	Quiz result (%)	*Adaptation result*	*Result*
1	80-100%	Proceed while reorganizing the learning contents with less details	OK
1	60-80%	Continue in the normal flow	OK
1	40-60%	Proceed while reorganizing the learning contents with simpler details – addition of animation & pictures is seen	OK
1	20-40%	Simplifies further the learning contents as learner performance level drops (more basic content types are seen such as images, captions, simple texts)	OK
1	0-20%	Stops and starts over the learning process with the simplest and elementary content elements	OK

The application so far provided results which were in line with the Cognitive Level test case introduced. Learners were able to identify their actual status of their performances through the adaptation rules set.

VI. CONCLUSIONS

The development of personalized and adaptive learning application using instant context information through various mobile devices has recently gain a lot of attention. Real-time adaptation is the proud base to build a context-sensitive mobile application. The context-aware mobile learning application has been considered as an initial step towards formulating a content-adaptation system for personalized learning. Various contextual information were successfully retrieved to deliver different self-adapted learning objects based on the learners' choices and his/her immediate physical conditions. The context-aware mobile learning system can further be extended to interpret many more contextual parameters at diverse heights merging the internal context types (motivation, comprehension level, feelings or moods) of the learner to enhance their learning experiences. For instance, the eye movement of the user while reading can be used to further adapt the learning contents. Scenarios such as having the eye of the learner on-screen should load varied contents based on the present situation. Other possible strategies are to track the comprehension level of the learner after each lesson. This needs further investigation for implementation to bring out a satisfactory and appreciative learning practice during study sessions.

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