Semantic retrieval: multiple response model for context-aware learning services

Xinyou Zhao*
Advanced Research Center for Human Sciences,
Waseda University,
Tokorozawa, 359-1192, Japan
E-mail: totoyou@ieee.org
*Corresponding author

Qun Jin
Faculty of Human Sciences,
Waseda University,
Tokorozawa, 359-1192, Japan
E-mail: jin@waseda.jp

Toshio Okamoto
Graduate School of Information Systems,
The University of Electro-Communications,
Tokyo, 182-8585, Japan
E-mail: okamoto@ai.is.uec.ac.jp

Abstract: With the consistent adoption of pervasive computing thoroughly integrated into our daily learning activities, seamless learning services can be provided for learners corresponding to their needs at any time and any place. The adapted learning service is delivered to learners based on learning situations and learning response/feedback, which are success and failure in practice. But because the learning needs are changing under available rich contexts, learning services generally make the learners ‘cognition overloads’ and ‘disoriented’ under context-aware ubiquitous learning environments. In order to deliver the most suitable learning service, this paper proposes a multiple response approach to realise context-aware learning services under pervasive learning environments. Based on six learning statuses from sharable content object reference model (SCORM), six responses of learning feedback are used to reward or penalise the preferred learning service according to the learning context. Experimental results show that the proposed methods perform well in practice and the prototype system can successfully deliver the learning services adapted to the learning contextual situations of learners.

Keywords: ubiquitous learning; mobile learning; pervasive computing; group learning; learning as a service.

Xinyou Zhao graduated from Xinyang Normal University in 2000 and obtained Master Degree of Computer Science from Guilin University of Electronic Technology, China, in 2003. In September 2010, he was awarded a PhD from Graduate School of Information Systems, The University of Electro-Communications, Tokyo, Japan. He worked as a Lecturer at Guilin University of Electronic Technology from 2003 to 2007. During 2005 to 2006, he was also a Visiting Scholar in Waseda University, Tokyo, Japan. Now, he is working at ACARIC Co. Ltd as a system engineer, Tokyo, Japan. He is also a Guest Researcher in Advanced Research Center for Human Sciences, Waseda University, Tokorozawa, Japan. He is currently serving as an Editor-in-Chief of the *IEEE Multidisciplinary Engineering Education Magazine (MEEM)*. His research interests include mobile learning, data mining, intelligent tutoring system and multimedia technology.

Qun Jin is a tenured Full Professor in the Networked Information Systems Laboratory, Department of Human Informatics and Cognitive Sciences, Faculty of Human Sciences, Waseda University, Japan. He was engaged extensively in research work in computer science, information systems, and social and human informatics. He seeks to exploit the rich interdependence between theory and practice in his work with interdisciplinary and integrated approaches. His recent research interests include behavior and cognitive informatics, user modelling, social network analysis, human-computer interaction, user-centric service computing, information search, recommendation and sharing, and e-learning.

Toshio Okamoto graduated from the Graduated School of Tokyo Gakugei University in 1974. He earned a PhD from Tokyo Institute of Technology in 1987. At present he is a Full Professor in the Graduate School of Information Systems, University of Electro-Communications (UEC), Tokyo, Japan. At UEC, he is also the Director of the Promotion Centre of e-Learning. He also holds the title of President for the Japanese society for Information and Systems on Education and the Japanese Association for Developing Information-Education. His areas of research include but are not limited to e-learning, educational technology, methodology of ICT utilisation in education, curriculum development, computer-based collaborative learning (CBCL), computer-supported collaborative learning (CSCL), and artificial intelligence (AI).

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1 Introduction

With the rapid development of communications and pervasive computing technologies, ubiquitous network society has emerged around us, e.g., u-Japan, u-Korea, and u-Home (Bell and Dourish, 2007; Yamazaki, 2007). Emerging ubiquitous computing and networking technologies have been increasingly integrated into many facets of our activities in daily living, including education or training (Esra et al., 2008; Zhao and Okamoto, 2011).
Benefitted from information visualisation in a detailed, interactive, coherent, and well-defined way (Jaescke et al., 2005), variously formal or informal learning services are being provided on digital devices based on the highly graphical, sophisticated schemes (Matt and Gary, 2006). Learning service publishers may deliver different kinds of human-centred services in real time. As a result, the learners may conveniently retrieve or explore fruitful learning services or rich media contents by personal computers or ubiquitous devices whenever they need (Zhao and Jin, 2011).

Most learning services have evolved from one-size-fits-all system to the adaptive learning system based on learning style and cognitive state (Dey et al., 2001; Economides, 2006; Sicilia and García, 2003). Learners are empowered with these learning services since the learning service system can provide adaptive learning service and interaction with their ubiquitous devices whenever they need and wherever they are in pervasive learning environments (Mohamed, 2009). In other words, the most suitable contextual learning services and contents should be delivered to learners whenever they are, and whenever they need (Jin et al., 2011; Zhao and Jin, 2011).

Another, because of the access restrictions of the personal computers, portable ubiquitous devices with no access limitation – such as laptops, iPods, iPads, personal digital assistants (PDA), or cell phones – are an ideal tool to provide a seamless learning service at any place and any time for learners and instructors through wireless access points (Su et al., 2011).

Benefiting from these modern pervasive intelligent technologies, the learners may improve their learning process and output by pictures taken by cameras, sounds recorded by recorders, online discussions shared with learning peers among a virtual learning community (Bell and Dourish, 2007; Velibor et al., 2011). Similarly, the instructors may also deliver or edit rich media teaching contents or learning objects, or can even create a real-time interactive community to help learners to resolve problems.

With mobile terminals and personal computers, learners may access learning services and learning materials in seamless learning ways with what they want. Seamless learning means that learning services should not be interrupted from place to place by any different device as what they need. The learning system can even provide more personalised learning services based on ubiquitous context recognition, such as learning location, moving speed, or the population density around learners. Therefore, seamless learning services are integrated and provided to gain the most satisfaction as pertinent as possible to learners’ activities, thoughts, and needs in real time (Jin et al., 2011).

With various contextual learning situations, the personalised learning needs are changing dynamically (Chen et al., 2010; Luis and Frank, 2000). That means, benefiting from available contextual learning information, learners should have a complete control over at their own paces when they want to study and from which location they want to study (Su et al., 2011).

Due to the heterogeneous nature of ubiquitous learning situations, the delivery of learning services becomes subject to more and more requirements and complicated. The preferences and needs of learning vary greatly because each learner is an individual student, situated with his or her individualised learning behaviours and preferences under his or her learning situation (Su et al., 2011).

As a result, these services are sometimes making the learners ‘cognition overloads’ and ‘disoriented’ under the contextual learning environments (Chen and Zhang, 2008). It
is still difficult to provide adaptive learning service with the maximum of the end learner experience till now (Velibor et al., 2011).

The learning service system needs a high-degree intelligent method to deliver a contextual learning service based on the learning situation, which is necessary to maximise the quality of learning experience and to achieve the desired learning outcomes under the prosumers (service producer and consumer) constraints of learners or participants (Christina and Patrik, 2010; Jin et al., 2011; Komoski, 2007; Velibor et al., 2011).

After the learning management system (LMS) incorporates historical learning records (ubiquitous device profiles, various learning preferences etc.) with the context awareness, the most adequate services are delivered to learners, which may be divided into different levels, such as a content service, a presentation service, or a transcoding service (Luis and Frank, 2000; Su et al., 2011; Zhao and Okamoto, 2011). Finally, the learning system ensures that the learning service is provided based on learning needs, rather than what the instructors find interesting (Longmire, 2011; Parrish, 2004).

The learning service, which is created based on previous learning feedbacks, can be successfully delivered to a learner according to his or her learning situation. In this paper, the main focuses are on how to efficiently provide the context-aware learning service in ubiquitous learning environments (ULE) based on historical learning experiences in order to meet the individual needs under the various contextual learning situations.

To achieve this goal, the learning relationships are ranked based on positive and negative responses. The positive responses are used to reward the learning historical records, and on the contrary, the negative response to penalise the learning experiences. The learning service, whose relationship rank is the highest among all clustered adapted services, is delivered to learners.

The rest of this paper is organised as follows. Adaptive learning service is discussed in Section 2. The issues on providing ubiquitous learning services are also introduced. Section 3 proposes the method to realise the adaptive learning service based on contextual data. Section 4 discusses an application scenario and the evaluation of the proposed method. Finally, Section 5 summarises our present work and points to the future research works.

2 Adaptive learning service

Recent advances of pervasive computing technologies and proliferation of multimedia mobile devices have further stimulated the development of intelligent pervasive multimedia applications (Hassanien et al., 2009). As a result, there are many successful applications introduced and applied by using a personal computer or ubiquitous device, e.g., e-learning service (Kojiri et al., 2007; Mohamed, 2009; Sharples, 2007; Shute and Towle, 2003).

But in fact, the general learning system designed based on personal computers system is not suitable for ubiquitous contextual situation because learners’ needs are always conditioned by what they have already got with context awareness (Germanakos and Mourlas, 2008). Today there are still more important problems existing in order to alter these learning applications to ubiquitous environment, such as how to precisely determine learning needs (Esra et al., 2008; Germanakos and Mourlas, 2008; Hsiao et al., 2008; Su et al., 2011), learning styles (Chen and Zhang, 2008), learning goals (Man et al., 2010)
or how to deliver context-based services in a learner-friendly and effective way (Chen et al., 2010; Luis and Frank, 2000; Velibor et al., 2011; Yang et al., 2007).

2.1 Adaptive services in learning system

In accordance with the exigencies of learning situations and management of limited learning resources dynamically, the adaptability of learning service is to provide contextual learning service adapted to learning skills, styles, behaviours, knowledge backgrounds, or motivations.

At this point, adapted learning service for a learner, including what he or she has studied and how much he or she has learned, is entered into historical records for future reference. Thus, from a technological point of view, the main challenge for adaptive services lies in correctly identifying general and specific characteristics for a particular learner to improve learning experiences under a ubiquitous learning situation (Shute and Towle, 2003).

The characteristics may be knowledge, skills, cognitive abilities, learning process/history and styles, learning preference, and so on, which will be referred by learning feedbacks in both formal and informal learning environments. Based on learning characteristics, the adaptive learning service system delivers right learning service customised to a learning’s needs and characteristics, such as in terms of knowledge level, preferences, and learning style (Kim and Choi, 2010), at right time in the appropriate way – any time, any place, any path, and any pace. The process of adaptive learning service is divided into two steps in general (Luis and Frank, 2000; Velibor et al., 2011; Zhao and Jin, 2011):

Step 1 Adaptation to learning characteristics. The LMS, like general e-learning system, creates adaptive services for learners, which is implemented based on adaptive behaviour according to learning context awareness. In other words, this process suggests the most suitable service for learners within available service and learning situation. The suggested services may be learning content link or place, which will not be delivered to learners directly.

Step 2 Adaptation to learning situation. With adaptation suggestion for adaptive services (e.g., learning link, place etc.), the LMS reconstructs recommended original services (information, contents, etc.) into adapted services, which are most suitable to network features with limited bandwidth, handheld devices with limited resources and computing capabilities, or learning location, etc.

2.2 Issues for providing ubiquitous learning service

With the heterogeneous proliferation of mobile devices, the deliveries of learning services on such devices become subject to more and more requirements (Barbosa et al., 2008; Su et al., 2011). Learners get a poor learning experience or activity in ubiquitous learning environment for the reason of great diversities which may be mobile device’s specification, learning service presentation, learning context (Luis and Frank, 2000; Velibor et al., 2011; Zhao and Okamoto, 2011).

The dynamical and continual changing learning situations in ubiquitous learning environment give more diverse learning contexts than those in e-learning based on
personal computers. Learning contexts are collected to provide information on the context in which learning behaviour or other experiences take places. The task of context awareness in ubiquitous learning is to detect the ubiquitous situation and adapt learning services to the diverse contextual learning environment (Conlan et al., 2002).

The contextual data may be collected from learner, learning environment, instructor, educational strategy, assessment methods, and so forth. Context awareness, which must be integrated into a learning system seamlessly, is the key in the context-aware learning service system. Figure 1 shows the learning context used in ubiquitous learning system, which are divided into four categories in general:

- device capabilities (DC), codec capabilities; input-output capabilities; device features; and JavaScript-enabled
- network characteristics (NC), static network features; and dynamical network conditions
- learning characteristics (LC), learning location; learning time; learning situation; and social awareness
- learning environment (LE), learner information; learning process; available learning service; and presentation preferences.

**Figure 1** Categories of contexts in ubiquitous learning system (see online version for colours)

![Diagram of contexts in ubiquitous learning system](image)

### 3 Multiple response model

In general, one learning response, which can be extracted from learning logfiles, is used to reward or penalise learning service based on learning feedback and learning situation from learners. The learning responses are divided into two categories: successes and failures.

If the learning response meets with favourable consequence (success), the selected learning service is positively reinforced for future learning provision. On the contrary, if the learning response meets with unfavourable consequence (failure), the learning system penalises the selected learning service. Economides (1996) calls the process reward-penalise method, which can formally be represented by Formula (1).

\[
\begin{align*}
\text{Reward} & \leftarrow \text{Success} \\
\text{Penalise} & \leftarrow \text{Failure}
\end{align*}
\]

(1)

But in fact, in any given learning situation, the learning feedback may be in a variety of ways if the first delivery does not immediately lead to a more satisfying learning state.
(Thorndike, 1911). So the learning responses from learners are not just the success or failure state, which are called multiple responses (Bernstein and Ebbesen, 1978; Economides, 1996; Thorndike, 1911). This research also introduces multiple response model for single reward-penalise model to improve the adaptation precision based on how much favourable (or unfavourable) the learning feedback is.

At a learning application system, the learning services are defined by $S = \{s_0, s_1, s_2, ..., s_n\}$. Supposed $C = \{c_1, c_2, ..., c_m\}$ as all context used in the learning service, the current context $U_c = \{c_i | c_i \in C, i \leq |C|\} \subseteq C$ are recognised or sensed by the ubiquitous learning system, which may be from sensor, GPS, camera or other tools (Zhao and Jin, 2011).

Under the current contextual learning environment ($U_c$), the available service ($U_i$) is denoted by $U_S = \{s_i | s_i \in S, i \leq n\} \subseteq S$. The possible successive service ($s_{i+1}$) of learning service ($s_i$) is determined by the probability of each adjacent learning service $s_x(s_i, s_{i+1}) \in S$, which is written as $p(s_x)$.

Let $R(s_0, U_i) \subseteq S$ denote the reachable set from $s_0$, which is the set of all learning services that are reached by any trajectories that start at $s_0$. This can be denoted formally in Formula (2).

$$R(s_0, U_S) = \{s_i | s_0, \exists \exists c_i \in U_C, p_x(s_i) > 0\}$$

The process is described in Figure 2, in which $r(s_{i-1}, s_i) \in R$ means that $s_i$ is reachable from $s_{i-1}$. Among all available learning services $R(s_n, U_i)$, the probability $P(r(s_n, s_{i+1}))$ has a maximum value among all reachable services $U_i$. The learning service $s_{i+1}$ is looked as next service for $s_i$.

![Figure 2 Learning service process](image)

In this research, the reward-penalise method adopts different adaptation rate for different learning response. If the historical learning feedback is in a favourable environment response, the probability $p_x(s_i)$ is increased by increasing rate $\Delta p_x(s_i)$ and $p_x(s_j) (j \neq i)$ is decreased by decreasing rate $\Delta p_x(s_j)$ at learning state $t$. Otherwise, if unfavourable environment response appears, $p_x(s_i)$ is decreased by $\Delta p_x(s_i)$ and $p_x(s_j) (j \neq i)$ is increased by $\Delta p_x(s_j)$. The final learning service is delivered based on $p_x(s_k), 0 \leq k \leq |U_i|$. 

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The $\Delta p_i(s_i)$ and $\Delta p'_i(s_i)$ are the increasing adaptation rate and decreasing adaptation rate separately, which the $\Delta p_i(s_i)$ may be equal to $\Delta p'_i(s_i)$ if there is only two learning responses (success and failure) used in learning application environment. During each step, the reward or penalise computing of $p_i(s_i)$ is shown in Formulas (3) and (4).

Learning service transition $r(s_i, s_j) \in R$ received positive response in Formula 3.

$$
\begin{align*}
    p_i(s_j) &= p_i(s_i) + \Delta p_i(s_i)(1 - p_i(s_i)) \\
    p_i(s_k) &= p_i(s_k)(1 - \Delta p_i(s_k)), k \neq j
\end{align*}
$$

(3)

Learning service transition $r(s_i, s_j) \in R$ received negative response in Formula 4.

$$
\begin{align*}
    p_i(s_j) &= p_i(s_i) + \Delta p'_i(s_i)(1 - p_i(s_i)) \\
    p_i(s_k) &= p_i(s_k)(1 + \Delta p'_i(s_k)), k \neq j
\end{align*}
$$

(4)

According to six status values of SCORM (2004) data model definition (passed, failed, completed, uncompleted, not attempted, and browsed), the learning responses in this research are defined by six statuses in Table 1 ($R$: reward, $P$: penalise). All six learning statuses are defined based on the learning responses. For example, the learning response in P2 is looked as failure because the learner has to change another learning service instantly. The system will penalise this learning process for future. On the contrary, the system will take the learning process as passed status (R2) if the learner goes on another learning service after he/she has accessed one learning service.

<table>
<thead>
<tr>
<th>Type</th>
<th>Events (status)</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>R2</td>
<td>Learn, then go on next learning service (passed)</td>
<td>Reward</td>
</tr>
<tr>
<td>R1</td>
<td>Learn and stop (completed)</td>
<td>Reward</td>
</tr>
<tr>
<td>R0</td>
<td>Never use learning service (not attempted)</td>
<td>Reward</td>
</tr>
<tr>
<td>P0</td>
<td>Use, but change another format of same service or access again for the same service (browsed)</td>
<td>Penalise</td>
</tr>
<tr>
<td>P1</td>
<td>Instantly change another format of same service (incomplete)</td>
<td>Penalise</td>
</tr>
<tr>
<td>P2</td>
<td>Instantly return same learning service (failed)</td>
<td>Penalise</td>
</tr>
</tbody>
</table>

Another, it is difficult to provide new items or new users in recommendation or personalised application system (Chen et al., 2010) because the application system knows less about them. In this research, the R0 is the threshold for a favourable response to reward the new services in order to rank the service recommendation rate.

For different web-based educational service systems, the learners may access different service (e.g., self-selected service, recommended service, etc.) based on their knowledge background and learning context. For example, in order to provide learning service for primary school education, the system had better recommend or suggest suitable preferred learning service for a new learner or a novice usually. In other words, the system should use a higher weight of service response from recommended learning service than those from self-chosen learning service. On the contrary, for adult or expert, they can determine the learning service by themselves under their knowledge structure.
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and learning situation, which means that response of self-selected services are more important than those from recommended services.

So the system cannot take the response of the recommended and self-selected services as same weight for the adaptive learning application. Service responses should consider different weight for different applications system. Under the learning context $U_c$, all accessed services are divided into two categories: recommended and self-selected services. The system assigns $\alpha$ to learning service that is recommended, while $1 - \alpha$ is assigned to learning service that is self-selected.

Different $\alpha$ may be used in different learning application system. They are represented in Formula (5). In general, the Formula (6) uses 0.5 as the threshold of $\alpha$, which means all accessed services have a same weight.

$$
\delta(\alpha, \gamma) \begin{cases} 
\alpha, & \text{(Recommended)} \\
1 - \alpha, & \text{(Self-selected)} 
\end{cases} 
0 \leq \alpha \leq 1
$$

(5)

$$\alpha = \begin{cases} 
\geq 0.5, & \text{High Priority} \\
= 0.5, & \text{Same Priority} \\
\leq 0.5, & \text{Low Priority} 
\end{cases}
$$

(6)

Based on the discussion of the multiple-response reward-penalise methods above, the initial probability of $P(s_i)$ under $U_c$ is formally defined by Formula (7).

$$
P_r(s_i, s_j) = \frac{\sum_{k=1}^{m} R_{r(s_i, s_j)} \times p_{r}(s_j) \times \delta_{s_i}}{\sum_{k=1}^{m} \sum_{s_j} R_{r(s_i, s_j)} \times p_{r}(s_k) \times \delta_{s_i}'}
$$

(7)

$$R_{r(s_i, s_j)} = \begin{cases} 
\frac{1}{\|s_i\|} & \|s_i\| > 0 \\
1 & \text{others}
\end{cases}
$$

4 Evaluation

4.1 Ubiquitous learning scene

Suppose there is one u-learning scene – Sam will attend a final course examination at 9:30 today. Sam may go on reviewing by different ways to consolidate what he has learned before examination. The learning situation in Figure 3 is divides into five periods:

1. study by text book or personal computer at home
2. study by mobile device while riding a bicycle
3. study by mobile device or text book while taking train
4. study by mobile device while walking
5. study by personal computer at school.
(1) and (5) may be considered as e-learning and (2), (3), and (4) as mobile learning in general.

Figure 3 Ubiquitous learning scene

With the learning situation and context, the learning system may deliver suitable presentation format for Sam according to his learning situation. For example, the system may provide the learning service based on audio while riding a bike.

4.2 System architecture

In order to evaluate the adaptation mechanism proposed, the developed realisation model has been installed on a web system, which provides a general searching service for users. In the experimental evaluation system, the accessed items, time, location and device type are considered as learning context. The system provides types of contents such as text, image, document, and audio according to user’s experience. The model is shown in Figure 4.

Figure 4 Role of reward-penalise model
The context recognition module provides the context aware data, which are refined from various detection terminals, such as sensors, cameras (Zhao and Jin, 2011). Based on context data, the learning service module recommends the available service for current learning situation. Finally, the reward-penalise module delivers contextual learning service according to learning context, learning historical data, and available learning service.

4.3 System evaluation

Figure 5 shows all accessing reports of users between April 19 and 27, 2010, which concludes the visitors, page views (PV), average page views, visiting time per visit and average time per page (AT). Here the average time including the downloading and viewing/using time from each user.

During tracing, users are separated into two groups randomly: controlled group I for adaptation contents and non-controlled group II for general contents.

For controlled group I, the system creates adapted contents according to user’s ubiquitous environment. For example, the system would provide audio type if there were more users to use audio under same contextual environment even though the contents were text message. For non-controlled group II, the system just sends originally accessing contents for users.

The increasing rate of page view and visiting time between group I and II is computed by (I-II)/II (I or II means the access time (T) or page (P) from group I or II).

Figure 6 shows that page view growth rate ((PV_I-PV_II)/PV_II) between group I and group II are within [12% (April 25), 63% (April 27)]. For example, there are 3.95 pages accessed by each user from group I on April 19, 2010. Corresponding to group I, each user from group II visited 3.28 pages, whose growth rate: (3.95–3.28)/3.28 = 20%.

Figure 6 also shows that the total time (=PV × AT/visit) visiting from group I is more than that from group II. In addition, the users from group I may stay longer on each page.
than those from group II, whose growth rate \(\frac{(AT_I/PI-AT_{II}/PI)}{AT_{II}/PI}\) are within [10\% (April 22), 58\% (April 19)], which is shown in Figure 6.

**Figure 6** Increasing rate of time and page view between groups I and II (see online version for colours)

The results of PV and AT show that the users from controlled groups are more interested in their accessed contents and our proposed method may improve the utilisation rate of contents for web users. In other words, the learning service is most suitable to the learners’ need under their learning situation.

## 5 Conclusions

This paper presented an approach to reward-penalise the context-aware learning service with the goal of improving learning service performance automatically. The key insight of this paper is that multiple responses are used to deliver adaptive learning service according to his or her pervasive learning situations. Based on positive response and negative response of six learning responses in learning services, the multiple-response reward-penalise method proposed delivers context-aware learning service to meet the individual needs dynamically. Furthermore, the proposed method adopts different weights for contextual learning services based on a learner’s knowledge structure to improve the precision of learning service.

In the evaluation experiment, the preferred media formats of accessed learning objects have been used as a contextual learning service and the learning object, time, location and mobile device were mainly used as input of contextual data. With the comparison between the controlled group and non-controlled group, usability evaluation results of learning objects reveal that the adapted learning objects generated with multiple response methods proposed are more useful or interested than those from general learning service methods. Evaluation results show that the methods perform well in the learning
application, which can successfully deliver the context-aware learning services to learners according to the learning contextual situations.

As for future work, we will tackle the specific research question concerning ‘types of contextual information and sources’ using in u-learning environment. It is a challenging work to define/reason different context (physical context, time context, learner context, resources context) and describe the learning environment (capabilities of ubiquitous device, characteristics network and learner) during moving. In addition, we realise it is important that service adaptation is required to provide a universal access from e-learning content provider or the internet by ubiquitous device. The adapted services should be designed to maximise the learner’s quality of experience (QoE). The system should decide how to react while learning context is changing and how to select the appropriate adaptation and service parameters.

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