Adaptive Content Delivery Based on Contextual and Situational Model

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Adaptive Content Delivery Based on Contextual and Situational Model

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文脈と状況モデルに基づく適応コンテンツ配信に関する研究

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概要

数多くの教員が ICT を用いたフィールド学習（ユビキタス学習）を行っているが、学校の支援体制や活用可能なリソースが不十分でうまくいかないことが多い。

e-Learning システムは教材の共有を可能にするが、ほとんどの教材が高速ネットワークに接続されたデスクトップあるいはノートパソコンを想定して設計されており、低速ネットワーク接続の携帯端末に対応していない。従って携帯端末での e-Learning コンテンツへのアクセスは、期待されているほど使いやすいものにはなっていない。

本研究は、柔軟に拡張性の高い構造を持つ動的な共通のフレームワーク内でアダプティヴコンテンツを配信することを目標としている。これにより、文脈データやコンテンツ、優先メディアタイプのようなもので定まる学習者の文脈認識に沿って、動的に教育用コンテンツを再コード化あるいは再構築する適応型スキームを定義することができる。本論文は、ユビキタス携帯端末上での e-Learning コンテンツの利便性を向上させるための３つのサービスから成る。（１）、コンテンツサービス、（２）、コード変換サービス、（３）、表示サービスである。

本研究はユビキタスな学習環境の中で文脈認識に合わせた学習システムをデザインし、実行することに焦点を当てている。そこで我々は、並列プロダクションシステム（２つのワーキングメモリーを用いて、「文脈」と「状況」を処理する）を提案し、学習の文脈と状況に合わせた e-Learning コンテンツを動的に変換する。文脈メソッドは多様的報酬罰則反応アルゴリズムを用いて、優先メディアタイプのような学習嗜好性を定めるものである。状況メソ

ッドは交渉アルゴリズムを用いてデバイスやネットワーク、優先メディアタイプのような学習文脈に従って適合するコンテンツを提供するものである。インタプリタはReteアルゴリズムを用いてアクセスされるコンテンツの最終形式を決定する。

変換サービスはオリジナルのコンテンツ—それらは携帯電話や携帯端末のために設計されていない。従って適切に表示できない、もしくは適切に蓄積されない—を分析し、携帯端末で利用できる形式に変換する。ここで提案するFFSM (Feature Finite State Machine)法を用いた変換サービスに基づくキャッチングメカニズムは変換時間を短縮する。

表示サービスは遠く離れた学習者に登録されたコンテンツの中で学習文脈や状況に適合したものをプッシュ型で送り出すものである。

最後に、ユビキタス端末上の標準文書などのいくつかの事例を用いて、本研究で提案したメソッドの適合性を評価した。評価実験の結果、適合のプロセスは低いレベルのコンピュータリソースや素早いレスポンスなどのシステム要求を満足するものである。本研究によってe-Learningシステムを用いて時間や場所、デバイスの種類を問わずにシームレスな学習を提供することができるようになり、ユビキタス学習環境での学習経験が向上したことが評価実験から明らかになった。

Adaptive Content Delivery Based on Contextual and Situational Model

Xinyou Zhao

Abstract

Much of what has been written about teachers conducting field trips (ubiquitous learning) has been anecdotal. But at most times, the learning processes have to be interrupted during field trips because of lack of support from school administrations and inadequacy of resources.

Although e-learning system may share the learning objects with ubiquitous learning, most of learning objects designed for desktop computers and high-speed network connections today, are not suitable for network features with low bandwidth and handheld devices with limited resources and computing capabilities. So up to now, access to e-learning objects by ubiquitous devices has not become as convenient as expected.

The objective of this research is to provide adaptive content delivery in a common dynamic and extensible framework in order to have scalable, flexible and extensible architecture, which can dynamically define an adaptation scheme that recodes/reconstructs learning objects according to context awareness of learners, such as context data, learning object, and learner's preference. The proposal is consisted of three services to improve the usability of e-Learning objects on ubiquitous device: 1, *content service*; 2, *transcoding service*; 3, *presentation service*.

The research in this thesis has concentrated on the issues of designing and implementing learning system that should meet the learning context awareness in ubiquitous learning environment. In this research, we propose a new method based on parallel production system (two working memories: context and situation), which dynamically transcodes the e-learning objects according to learning context and situation. Context method determines that the learning preference (preferred media type) by multiple-response reward-penalize algorithm and situation method provides

adaptive contents according to learning context (device, network, and preferred media type) by negotiation algorithm. Interpreter determines the final version of accessed contents by Rete algorithms. We call this process as content service.

The transcoding service analyzes the original learning objects (not written specifically for mobile phones and devices and thus not displayed properly or stored) and converts it into a mobile-ready format. The proposed caching mechanism based on proposed feature finite state machine (FFSM) in transcoding service reduces the transcoding time.

At last, the presentation service pushes recoded contents to remote learners, which contents are adaptive to learning context and situation.

Numerical examples (learning Chinese course and standard document on ubiquitous device) are given, and properties of the methods are examined at last. The experiment results show that the adaptation process satisfies the request of system (e.g. low computing resource, quick response, etc). Because the proposal can provide a seamless learning with e-learning system at any time and place with any device, the results show that the learning experience is improved in ubiquitous learning environment by this research.

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Chapter 1

Introduction

Objectives

This chapter explains:

- Research Scope
- Problem Consciousness
- Research Focus
- Research Outcomes
- Overview of Thesis

Overview

This chapter provides an overview on the main facets of the research in this thesis. First, the general scopes for the research are introduced. Some related applications on other fields are also discussed. Secondly, three questions considered in this research are discussed in brief. After that, the focus and contributions of this research are introduced. This chapter concludes describing the whole structure of this thesis at last.

1.1 Introduction

Much of what has been written about teachers conducting field trips has been anecdotal (Michie, 1998). Some similar quantitative studies of the attitudes of teachers towards field trips were also undertaken by Falk and Balling (1979), Fido and Gayford (1982) and Muse, Chiarelott and Davidman (1982).

Sorrentino and Bell (1970) reviewed texts and research articles by science educators, summarizing their reasons for taking field trips into five 'attributed values': providing first-hand experience, stimulating interest and motivation in science, giving meaning to learning and interrelationships, observation and perception skills, and personal (social) development.

Of course, negative attitudes of teachers revealed by the research are interrelated to lack of support from school administrations for field trips (Falk and Balling, 1979; Muse, Chiarelott and Davidman, 1982; Orion, 1993; Price and Hein, 1991) and inadequacy of resources and choice of venue (Orion, 1993; Price and Hein, 1991).

Another, one of the main characteristics of our life is constantly changing and moving, lately also integrated with an increasing desire for mobile usage of computing and communications (Tumasch, 2003). The trends may be from the rapid spread of laptops, cell phone, iPhone and other ubiquitous device. Another trend is the fast growing working and learning on the moving, not just at the office or school (Keegan, 2004; May, 2001). Ubiquitous device seems an ideal tool for participating in field trips at any place and any time.

The combination of location aware technologies and a contextual learning approach facilities learners to construct meaningful contextualization of concepts during field trips, which has proven learning benefits (Michie, 1998; Patten, Sa´nchez and Tangney, 2006). By the use of wireless technology, anyone can access information and learning materials at any time and any place by ubiquitous device. As a result, learners have complete control of when they want to study and from which location they want to study. With ubiquitous learning, learners will be empowered since they can learn from anywhere and at any time (Mohamed, 2009).

1.2 Research Scope

Since ubiquitous computing technology was first proposed by Weiser (1993), the capabilities of ubiquitous devices such as personal digital devices (PDAs), cell phone, portable computers and smart phone are increasing at a steady rate (Wikipedia, 2009). People can now learn/work anytime and anywhere using laptops, phones, and palm devices with wireless connectivity, an enabled hotspot or wireless network.

Now over 60% people around the world accessed the internet or equivalent mobile internet services such as WAP and i-Mode at least occasionally using a mobile phone rather than a personal computer by the end of 2008 (Esra, Niall and Martin, 2008; Wikipedia, 2009). According to IBM's Institute for Business Value, the number of mobile users will grow by 191 percent from 2006 to 2011 to reach approximately one billion users (IBM, 2009). Mobile devices are gradually becoming ubiquitous and helping us transcend many boundaries.

Cell phones can take pictures, record sounds, reveal location, and even measure the population density and moving speed of users. The ubiquitous devices have become increasingly integrated into many facets of our daily activities, including education (Esra, Niall and Martin, 2008; Wikipedia, 2009). For example, with text-messaging, government can go mobile, such as sending text message to pay parking tickets in Singapore, to pay income tax in Philippines, for suggestion to National People’s Congress in China and receiving text message for examination results in Kenya, tax amount in India (Sylvers, 2008).

Over the past ten years, ubiquitous learning has grown from a minor research interest to a set of significant projects in schools, workplaces, museums, cities and rural areas around the world (Sharples, 2007; Song, 2008; Stanescunew, 2008). In school or university, home, train, or walking, learners may access e-learning objects by their portable devices at any time and at any place or receive information about class or school news in real time, which is called ubiquitous learning or u-Learning(Jones and Jo, 2004).

Today the unified u-Learning system evolved from a singular SMS m-Learning system is shown in Fig.1.1. U-Learning can bridge the gap of mobile and desktop computing (Farooq, Schafer, Rosson and Carroll, 2002), which provides a seamless learning for learners, which means that learning process can not be interrupted. In other words, the learning process can be continuously conducted at any time & place with ubiquitous device (pda, cell phone, smartphone, iphone, etc), not just with personal computer at home or office.

Barak, Harward and Lerman (2007) state that students have high attitudes towards to the use of ubiquitous device, before, as well as after using them as a part of their learning processes. Also, the learners felt that the use of ubiquitous device helped them to understand learning objects better and encouraged teamwork and interactions among themselves. Most of them found learning with ubiquitous device to be enjoyable.

The early stage of u-Learning only supports instant message by SMS. Today e-Learning system may provide richer media for learners by mobile browser embedded in ubiquitous device.

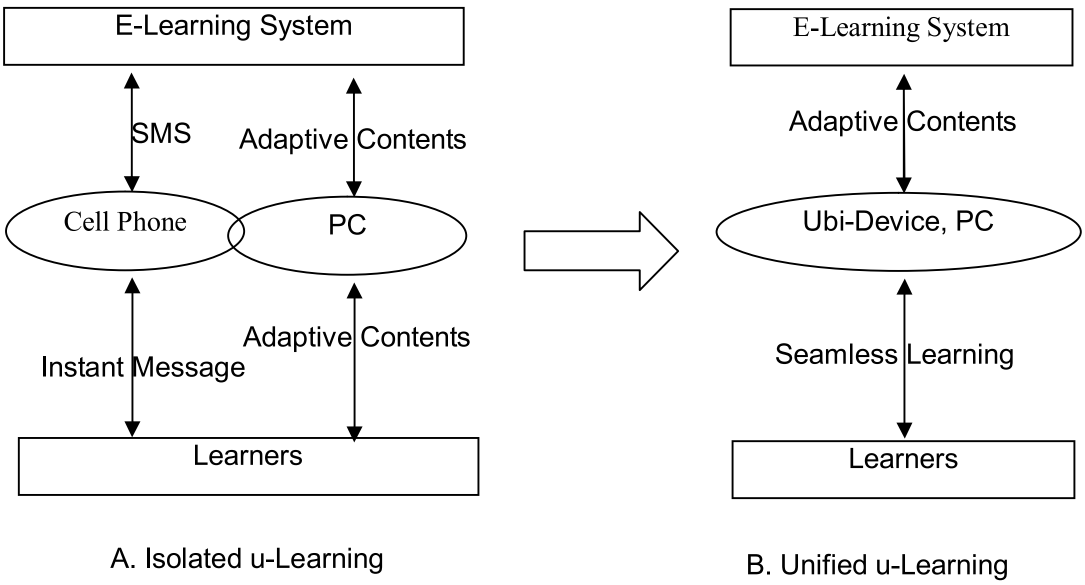


Fig.1.1 Evolution of u-Learning

Information visualization is a well-established discipline (Card, Mackinlay and Shneiderman, 1999). The highly graphical, sophisticated approaches have been proposed to provide vast sets of information for users. These graphical schemes have been applied to the fields of information retrieval and exploration in an attempt to overcome searching and accessing problems on conventional, large-screen displays (Matt and Gary, 2006). The users may conveniently access graphical information by personal computer.

IBM (2009) shows that 83% of the world that does not have easy access to the Web services via PCs. In order to compensate for the inadequate access limitation, many applications on personal computer, e.g. the successful e-Learning application, should also be altered to ubiquitous device. But some visualization schemes may not be appropriate for small-screen devices: even if the display technology can deliver the high resolution required, the available screen space is not necessarily adequate for meaningful presentations and manipulation by the user (Matt and Gary, 2006). Techniques and practices for delivering best possible learning experience for each mobile device are needed, even with widgets, webapps or offline web applications.

For example, rich contents can not be correctly displayed on mobile device (Kojiri, Tanaka and Watanabe, 2007; Yang, Chen and Chen, 2007); different needs under different learning location & time (Esra, Niall and Martin, 2008; Hsiao, Hung and Chen, 2008).

As a result, the learners get a bad learning experience during u-Learning environment because of the much diversity of device specification, learning objects, and mobile context existing today. At last, unified u-Learning easily makes learners drop out from e-learning system on mobile device because of much diversity in u-Learning environment (Sharples, 2007).

1.3 Problem Consciousness of Research

Most of learning objects, designed for desktop computers and high-speed network connections today, are not suitable for network features with low bandwidth and handheld devices with limited resources and computing capabilities.

As a result, the learners get a bad learning experience with ubiquitous device because of the contextual diversity, which also makes learners drop out from e-learning system on mobile device easily (Sharples, 2007). Delivering learning resources designed for tabletop computers to ubiquitous learning environment is still a challenging research issues today.

- In order to provide suitable learning objects on ubiquitous device and confirm the contents displayed on device correctly, the system should know the closest capabilities of ubiquitous device (MOBI, 2009; Woo and Jang 2008; Zhang, 2007);
- Massive amount of contents, irrelevant to learners' preferences or contextual environment, will make learners feel frustrated and dissatisfied (Evangelos, Elissavet and Anastasios, 2008; Wang, Wang and Huang, 2008). Also, more contents, irrelevant to learners' preference or not suitable for learning

environment, also increase the learners' communication costs and channel burdens (Yao and Wua, 2009). Last, mixed contents can not be played in general;

- It takes more time to realize the adaptive content delivery dynamically according to learning context (Zhang, 2007). Real-time transcoding is when the transcoding is being done on-the-fly or as the content is being played back. Transcoding will be required to be done in real-time to make a good learning experience as learners don't want to have to wait for hours to transcode content (Thomas, Yannis and Vana, 2009).;

Based on the problems above, the basic hypothesis of this research is that introducing adaptation mechanisms into e-Learning can improve the usability of e-Learning objects on ubiquitous device. The adaptive contents (S') are created according to the learning preference (L), content (S), and learning contexts & situation (C), in short, it is $\mathrm{Re}commendation(S \rightarrow S' | L, C)$, which is shown in Fig.1.2.

The adaptive contents (not just in text and image, also in document, audio) are recommended not only based on learners' preference, educational strategy, also based on learning context, such as device capabilities, learning time, learning location, et al.

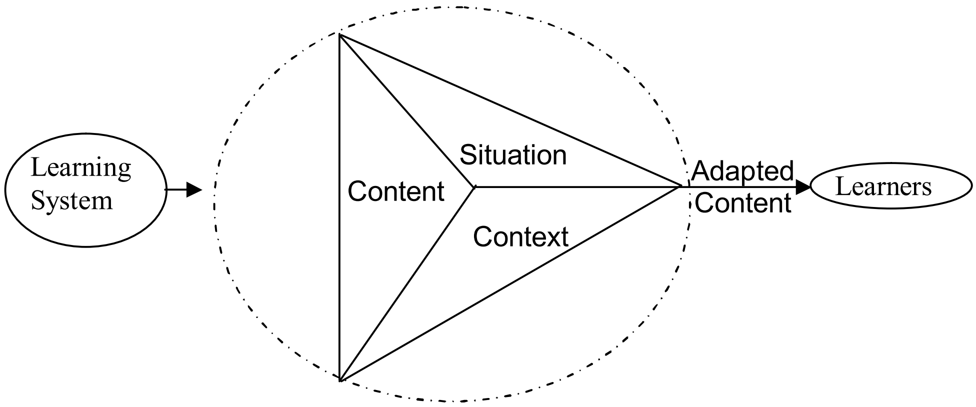


Fig.1.2 General Research Model

1.4 Research Focuses & Outcomes

In order to provide a seamless accessing for learners with ubiquitous device, the presented research in this thesis concentrates on the issue of designing and developing an adaptive content delivery system that introducing adaptation mechanism to e-learning system meets the requirement of context awareness, such as, the system uses browser detection to vary the size of the chunks from 8KB to 30KB depending on the capabilities of learner's browser. Our methods not only resize images, and break pages into smaller chunks which should work on most ubiquitous device, also transcode different learning rich media according to learning context. Therefore, special focuses are set on the following main research aims corresponding with research questions considered in this thesis.

1.4.1 General Research Focus

A ***How to get the* capabilities *of ubiquitous device in the running.*** A device database is updated everyday according to the learner's access. Based on that, an advanced detection method is proposed to detect more accurate features of mobile device used by learners. The features of device are applied on contents adaptation and transcoding process.

B ***How to reason the context to create adaptive contents according to learner's context* awareness**. A general contextual model is defined according to context awareness and learning situation. The learning history combined with identified context awareness is used to rank what adapted contents should be changed according to learning changing instantly.

C ***How to transcode original contents into adaptive contents according to context awareness***. A proposed adaptation mechanism recommends suitable version for original contents (a job-based solution approach), by which transcoding mechanism recodes original contents (text, image, audio and video) into really adapted contents. At last, really adapted contents embedded with suitable format, which are correctly displayed on target device, are pushed to learners.

1.4.2 Special Research Questions

A ***How is* possible *to detect the feature of mobile device when there is no information in database***. It is not possible to create a complete device database because there are many new device models appearing everyday. This research proposes a method to dynamically update the device profiles everyday and recommend most similar feature for device not stored on database.

B ***How is possible to transcode the learning objects on the fly***. In spite of the high consumption of time & resource for dynamical transcoding of learning objects, a caching technology has been proposed and implemented to realize transcoding in real time. With the increasing of request times from learners, the transcoding time fast decreases. Also, the computing resource will not appear bottle-neck of peak easily.

C ***How can the system framework create scalable adaptive contents for ubiquitous learning, which is implemented on an adaptive behavior according to learning context awareness.*** A so-called adaptation of learning objects modeling system has been proposed. The system is not an isolated system, rather easily combined with other e-learning system, which may get original contents from e-learning system and recommend adaptive contents according to learning context awareness.

1.4.3 Summary of Contributions

The technical outcome of the research is the adaptive contents for learners, who can access e-learning objects at any time and any place with any device. Also, the computing process needs low consumptions of time & resource. The proposed architecture has been designed, implemented, evaluated and improved.

Further, as main author or co-author, several parts of the chapters in this thesis have been published or in press in various non-peer-reviewed or peer-reviewed national conferences (in sum: 4 publications), various peer-reviewed international conference proceedings (in sum: 6 publications) and journals (in sum: 5 publications).

1.5 Overview of the Thesis

The structure of remainder of the thesis is as follows:

Chapter 2 presents general surveys of the research areas dealt with this thesis, which is adaptive content delivery in ubiquitous learning environment. First, the evolution of informal learning is discussed. The special features of m-learning and u-learning are discussed in details. Secondly, the adaptive learning techniques for general learning, e-learning and u-Learning are deeply discussed. Also, the main difference for adaptation between e-learning and u-learning is also given. Thirdly, the three main issues (diversity of mobile device, diversity of learning objects, and diversity of mobile context) in ubiquitous learning environment are also introduced briefly. Fourthly, the foundational method and theory of parallel production system (PPS) is introduced. Followed it, one of famous conflict set algorithms, the Rete match algorithm, is discussed. Thereafter, the strategy and classification of content adaptation are also discussed. Last, the related researches and device profiles are reviewed.

Chapter 3 proposes the architecture of adaptive content delivery in ubiquitous learning environment. First, learning context in ubiquitous environment is defined. Moreover, the benefits of mobile context are given. Another, the ubiquitous learning environment according to research context is defined. Secondly, the three level service models are proposed. Functionalities of each service are also explained in details. Thereafter, general architecture for adaptive content delivery is explained briefly. Also, five special features of our proposed methods are discussed at last.

Chapter 4 is mainly dedicated to presentation service according to the three service models proposed in Chapter 3. First, some related definitions are given for future adaptation. Secondly, the advanced detection methods for ubiquitous device capabilities are mainly presented and also compared with other mechanisms in this subsection. Finally, the presentation service mechanism is given. Some results are also presented.

Chapter 5 is mainly dedicated to another two adaptation services, adaptation service and transcoding service. First, adaptation mechanism is proposed. It contains three main functionalities components: adaptation decision module, contextual module and situational module. Situational module creates a Feature Finite State Machine (*FFSM*) for learning media component, which contains the feature transitions for adaptive contents. Contextual module recommends the preferred media type of accessed learning component media by using the multiple-response reward-penalize (MR-RP) method. Adaptation decision module determines the final transition jobs based on the ffsm for learning objects according to many different rule-bases by using of Rete match algorithms. Secondly, transcoding service recodes or reorganizes accessed learning objects into adapted contents according to transcoding jobs created by adaptation service.

This chapter also evaluates the performance of adaptation architecture proposed based on four issues: performance to ubiquitous learning environment, response time of transcoding, and learning experience from learners. The experiment results show that the transcoding process satisfies the request of system (e.g. quick response) and users' preference (e.g. more page views and page time). Also, the responses from testers show that learning experience is improved because the system can provide a seamless learning environment for learners.

The evaluations show that the proposed system can improve the usability of learning contents from e-learning system on ubiquitous learning environment.

Chapter 6 summarizes the concerning of the thesis and the three general contributions and three special contributions and proposes some recommendations for the future works and applications.

1.6 Summary

This chapter briefly discusses the main works in this research. After the general research scope introduced in brief, the problem consciousness concerned with the ubiquitous learning are discussed. Then, the research focus and contributions of this thesis are given. At last, the structure of the thesis is summarized in brief.

Next chapter will review the research background concerned with adaptation techniques in u-Learning environment in this thesis.

Chapter 2

Adaptation and u-Learning

Objectives

This chapter explains:

- Evolution of Education
- Adaptive Learning System
- Main Issues for Adaptive Content Delivery
- Parallel Production System
- Content Adaptation
- Reviews of Literature

Overview

This chapter explains the research background about ubiquitous learning techniques and questions concerned in this thesis. First, the evolution of education is discussed. In this section, mobile learning and ubiquitous learning are discussed in details. Secondly, the questions and difference of adaptation technology between e-Learning and u-Learning are introduced. Thirdly, three main issues of adaptive content delivery considered in this thesis are discussed. Fourthly, the elementary knowledge of Parallel Production System (PPS) is introduced. Thereafter, the general architecture, methods, and strategy of content adaptation are explained briefly. Lastly, the existing techniques of adaptive contents and profile model of ubiquitous device used in ubiquitous teaching-learning environment are reviewed.

2.1 Introduction

People use their mobile device not only as speech communication, but also as a powerful data communication tools today. The use of wireless, mobile portable, iPod, and handheld devices is gradually increasing and diversifying across every sector of education in the world. Now ubiquitous device is adopted to enhance learning or others used in classroom and the community (Motiwalla, 2007; Ogata, 2008), which is called ubiquitous learning (Sharples, 2007; Vicki and Jun 2004).

Mobile devices and techniques are pervasive and ubiquitous. It is possible to integrate the digital information with the physical environment. One important nature of ubiquitous learning is mobility. For each learner, the nature of mobility means that the learner has a variety of context while traveling, driving, or walking. Learning that used to be delivered “just-in-case” can now be delivered “just-in-time, just-enough, and just-for-me” (Motiwalla, 2007; Tomsons, 2007).

Ubiquitous learning using handheld computers is obviously immature in terms of both its technologies and its pedagogies (Mohamed, 2009; Sharples, 2007). In adaptive educational hypermedia, the focus is on the learner’s characteristics (Laroussi and Derycke, 2009). Although the e-Learning has evolved from one-size-fits-all system to adaptive learning system, the adaptive contents from e-Learning system are not suitable to study in ubiquitous learning environment because e-Learning system does not take into account their various contexts. The learner produces heterogeneous needs under various contexts although he/she is accessing the same learning object in ubiquitous learning environment. So besides learner’s characteristics, adaptation to learner’s contextual environment is a new kind of adaptation that was brought by e-Learning systems (Peter, 2001).

Another, because many of mobile devices can not display high-resolution graphics, transferring high-resolution images to those mobile devices is not feasible (Lum and Lau, 2003). Also, the problem is nontrivial as e-Learning contents are becoming increasingly rich varied in format and style. Content adaptation has been looked as a good resolution to tackle some of the problems from ubiquitous learning.

2.2 Evolution of Education

Education and training is the learning process by which the wisdom, knowledge and skills of generation are passed on to the next (Keegan, 2005). This education process has been going on since private school taught by Kongzi before 2500 years ago. Now the education has become the main force of social progress. There are two forms of education and training: formal education and non-formal education.

2.2.1 Formal Education

A formal education program is the process of training and developing people in knowledge, skills, mind, and character in a structured and certified program, which has three special characteristics shown in Table 2.1.

Table 2.1 Three Characteristics of Formal Education (Keegan, 2005)

- The teacher and learning group should be grouped at a fixed time in a fixed place for the purposes of learning
- The learner is members of the learning group
- Interpersonal communication is the means by which the learning process of education and training take place.

Education provided in the system of schools, colleges, universities and other formal educational institutions normally constitutes a continuous 'ladder' of fulltime education for children and young people, generally beginning at age five to seven and continuing up to 20 or 25 years old (UNESCO, 1997). In general, the learning process of formal education is also known as face-to-face education or ILT (instructor led training).

2.2.2 Non-Formal Education

UNESCO (1997) defines that any organized and sustained educational activities that do not correspond exactly to the definition of formal education. Non-formal education may therefore take place both within and outside educational institutions, and cater to persons of all ages. Learners may be from baby to one over 100-year-old people. Depending on country contexts, it may cover educational programs to impart adult literacy, basic education for out-of-school children, life-skills, work-skills, and general culture. Non-formal education programs do not necessarily follow the "ladder" system, and may have differing duration.

A D-Learning

D-Learning refers to distance learning or distance education. D-Learning, is a field of education that focuses on the pedagogy and andragogy, technology, and instructional systems design that aim to deliver education to students who are not physically "on site". It frees learners so that they may study at any time and any place. In practice, the learners are usually connected to the central lecture theatre by one-way video, two-way video etc. to study (Keegan, 2005).

B E-Learning

E-Learning (eLearning) is electronic learning. Communication technologies are generally categorized as asynchronous or synchronous. Based on communication technology and computer technology, it is used for web-based distance education, with no face-to-face interaction. It integrates and combines text, audio and video with interaction amongst participants.

Today, E-Learning system uses Web 2.0 technology to enhance, rather than replace, the physical pedagogical processes by relying more on collaboration, informal learning, and blended learning.

C M-Learning

M-Learning is mobile learning. From a technological standpoint, the term is used for learning that can be delivered and supported entirely by mobile technology. It is distinct in its focus on learning across contexts and learning with mobile devices. M-learning is convenient in the sense that it is accessible from virtually anywhere, which provides access to all the different learning materials available. Therefore, among the most common options that could be used for mobile learning would be PDA's, smart phones and of course, a wireless laptop.

For mobile learning, the first major difference with e-Learning is that it is un-tethered. It also is defined by learning that is more informal and opportunistic. Most importantly, mobile learning has the potential for even greater impacts than e-Learning.

Table 2.2 Relationship of m-Learning to e-Learning (Keegan, 2005)

Functionality		*Mobility*		
Computers	Laptop computers	PDA's Handhelds	Smart Phone	Mobile Phone
E-Learning		*M-Learning*		

For example, one major change in the idea of learning is that teachers used to deliver some material, or knowledge, with the idea that the student learns the concept "just-in-case". In fact, most of education is traditionally offered in such a format.

It is also collaborative; sharing is almost instantaneous among everyone using the same content, which leads to the reception of instant feedback and tips. In many cases, m-Learning is used to support e-Learning, for example when learners may not have quick access to non-movable technical devices such as desktop computers (Charmonman and Chorpothong, 2005).

The latest in technology means that a brand new focus is possible, that learning can be delivered "just-in-time." With the concept of student ownership critical to learning processes, we can see that the latter option should be far superior when working with a classroom full of students. Because not only can the learning be provided "just-in-time," it can be provided "just-enough" or even "just-for me." The learners may get a better learning experience in u-learning environment than e-learning environment.

Table 2.3 Delivering of Learning Contents (Tomsons, 2007)

E-Learning	M-Learning		
just-in-case	just-in-time	just-for me	just-enough

D U-Learning

U-Learning refers to ubiquitous learning. Education is happening all around the student but the student may not even be conscious of the learning process. Its learning environments can be accessed in various contexts and situations. Vicki and Jun (2004) define a ubiquitous learning environment (ULE), which is a situation or setting of pervasive education/learning.

The context in ULE is categorized into: ubiquitous (pervasive, omnipresent, and ever present, everywhere), learning (educational, instructive, didactic, and pedagogical) and environment (surroundings, setting, situation, and atmosphere). Some main characteristics, different to other learning forms, are shown in Table 2.4.

Table 2.4 Main Characteristics of Ubiquitous Learning (Ogata and Yano, 2003)

Permanency	Learners never lose their work unless it is purposefully deleted. In addition, all the learning processes are recorded continuously everyday
Accessibility	Learners have access to their documents, data, or videos from anywhere. That information is provided based on their requests. Therefore, the learning involved is self-directed
Immediacy	Wherever learners are, they can get any information immediately. Thus, learners can solve problems quickly. Otherwise, the learner can record the questions and look for the answer later
Interactivity	Learners can interact with experts, teachers, or peers in the form of synchronies or asynchronous communication. Hence, the experts are more reachable and the knowledge becomes more available
Situating of instructional activities	The learning could be embedded in our daily life. The problems encountered as well as the knowledge required are all presented in their natural and authentic forms. This helps learners notice the features of problem situations that make particular actions relevant
Adaptability	Learners can get the right information at the right place with the right way

2.3 Adaptive Learning System

The adaptive system is in the present a common and trendy concept with the field of computer science (Victor, 2007), e.g. artificial systems. Today there are distinct definitions in different academic subject or domains.

In general, an adaptive system is a set of interacting or interdependent entities, real or abstract, forming an integrated whole that together are able to respond to environmental changes or changes in the interacting parts, which changes in behavior of a person or group in response to new or modified surroundings. Every adaptive system converges to a state in which all kind of stimulation ceases (José, Javier and

Darío, 2009).

2.3.1 Adaptation Service in Learning

Arriving at the present and from the software engineering point of view, the user centric service is increasing more relevance within the research community (Victor, 2007). Within learner-centric adaptation system, Conlan, Hockemeyer, Wade and Albert (2002) state that adaptive services base their adaptivity on learner and context information, as well as on an encapsulation of the expertise that support the adaptation. Thus, the adaptivity and adaptability in e-learning systems is essential in order to adjust the changing of learner's situations dynamically. A formal definition of the law of adaptation is as follows:

Given an e-Learning system S, we say that a physical event E is a stimulus for the system S if and only if the probability $P(S \rightarrow S' | E)$ that the system suffers a change or be perturbed (in its elements or in its processes) when the event E occurs is strictly greater than the prior probability that S suffers a change independently of E (José, Javier and Darío, 2009):

$$P(S \rightarrow S' | E) > P(S \rightarrow S') \text{ ---Formula 2-1}$$

The Fig.2.1 gives different domains between adaptive e-Learning and u-Learning. From the Fig.2.1, we may know that we can provide more adaptive contents for learners according to more contextual data. Of course, learning experience will be improved at last.

The learning history or learners' profiles are used for adaptive contents in traditional e-Learning. In ubiquitous learning environment, more contexts (e.g. device capabilities, network feature, learning environment, et al.) are used to recommend adaptive contents besides learners' profile.

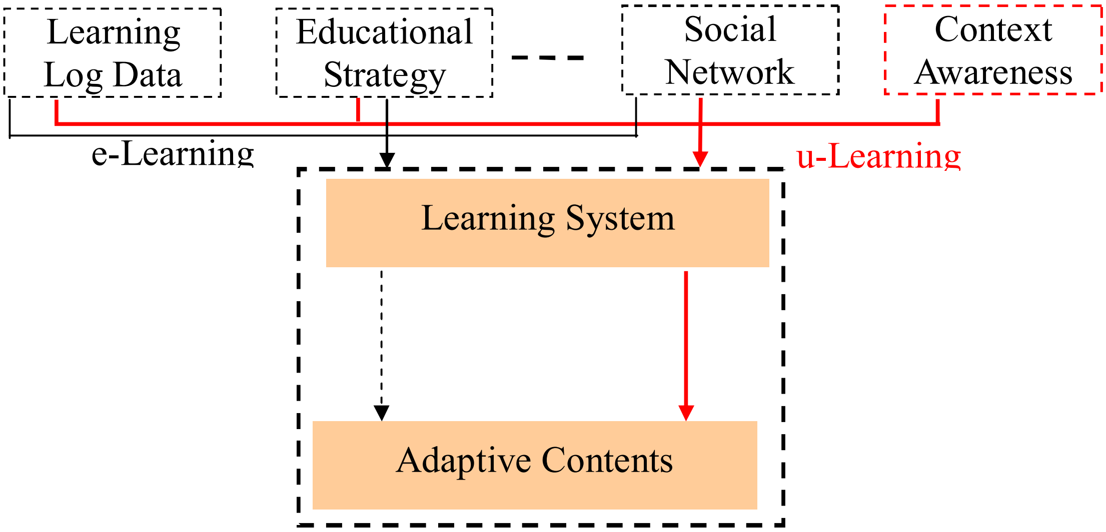


Fig.2.1 Different Domains in e-Learning and u-Learning

2.3.2 Adaptive Content in e-Learning

Today, the success of adaptive e-Learning system is due to the efficient delivery of learning contents by means of advanced personalization techniques. Thus, from the technological point of view, the main challenge of these personalization techniques depends on correctly identifying characteristics of a particular learner (Shute and Towle, 2003). The characteristics may be knowledge, skills, cognitive abilities, learning process/history and styles, learning preference, and so on (Shute, 1994; Snow, 1989; Ueno and Okamoto, 2007).

In short, enhancing learning and performance is a function of adapting instruction and content to suit the learner, in other words, the aim of adaptive e-Learning system is coordinated with actual education & learning: right learning contents at right learner at right time in the appropriate way – any time, any place, any path, any pace (NASBE, 2001). Usually, the adaptive e-Learning contents can be recommended by an adaptive engine given under learning content model, learner model, and instructional model (Shute and Towle, 2003).

2.3.3 Adaptive Content in u-Learning

The dynamical and continual changing learning setting in ubiquitous learning environment gives more different learning contexts than those in e-Learning. The task of context awareness in ubiquitous learning is to detect the ubiquitous situation and adapt to the changing context during learning (Chan, Sharples, Vavoula and Lonsdale, 2004). Context awareness is the key in the adaptive ubiquitous learning system (Malek, Laroussi and Derycke, 2006) and must be integrated with learning system truly (Lavoie, 2006).

The system framework creates adaptive contents for ubiquitous learning, which is implemented on an adaptive behavior according to learning context awareness. The main purpose of the adaptivity is to provide context awareness-based learning under learner's different skill and motivations. The contexts may be learner's state, educational activity, environment state, or system infrastructure et al (Economides, 2006). The works are completed by an adaptation engine in general. The adaptation engine uses context data of ubiquitous learning as input data to produces the adaptation results. The one of challenge is to exploit the changing environment with a new class of learning applications that can adapt to dynamic learning situations accordingly (Nagella and Govindarajulu, 2007). For example, the location, identity, time, and activity have been used as primary types of context in Schilit, Theimer and Welch (1993), physical and social environment, device state, cognitive, behavior and task as context in Schmidt, Beigl and Gellersen (1999).

Another challenge is to provide rich learning contents on mobile device, which has constrained capabilities. The system should consider more learning contexts than e-Learning system, such as connectivity, communication expense, device capabilities, learning locations et al (Rho, Cho and Hwang, 2005). According to context awareness, the system should dynamically transcode adaptive learning contents for learners into adapted contents on the fly.

In a word, the contents in ubiquitous learning environment are adaptive not only to learners' situation, also to learning contexts, which is shown in Fig.1.2.

2.4 Three Main Issues in Adaptive Content Delivery

With the development of communications, the 3G is coming and used in the world. Many applications on personal computer, e.g. the successful e-Learning application, have been altered to ubiquitous device too.

But some visualization schemes may not be appropriate for small-screen devices: even if the display technology can deliver the high resolution required, the available screen space is not necessarily adequate for meaningful presentations and manipulation by the user (Matt, 2006). So up to now, access to e-learning contents designed for desktop platform by mobile devices has not become as convenient as expected with mobile browser embedded in mobile devices (Chang, Hung, Wang, Weng, Shih and Lee, 2008; Kojiri, Tanaka and Watanabe, 2007; Yang, Chen and Chen, 2007).

Another, in ubiquitous learning environment, more released context can be detected and used. According to domains considered in adaptive u-learning and e-learning (Fig.2.1), the system may provide more adaptive contents in ubiquitous learning environment for learners. But it is still difficult for researchers how to reason or infer the context data for applications.

The Table 2.5 summarizes the diversity domains and features in ubiquitous learning environment.

Table 2.5 Different Diversity in u-Learning Environment

Type	Features
Devices	**Hardware**: memory, screen size, resolution, color depth… **Software:** supported media formats, mobile browser
Contents	**Text**: TEXT, PPT, DOC, PDF… **Image**: SVG, JPEG, GIF, PNG, WBMP… **Animation**: FLASH, GIF… **Audio/Video**: AMR, 3GP, EVRC …
Contexts	**Personal Context**: user's preferences, calm behavior… **Social Networks**: personal history, friends, blogs … **Other Context**: location, time …

2.4.1 Diversity of Mobile Device Specifications

The range and diversity of devices on the market today present a challenge to provide contents on mobile device for users. Even though the memory and computational capabilities of these devices will continue to improve, Erol, Berkner and Joshi (2008) and Hsiao, Hung and Chen (2008) show that the small display sizes and limited input capabilities for user interaction are likely to remain the major bottlenecks for many mobile applications.

The Table 2.6 and Fig.2.2 describe the status of mobile phone used in Japan from April 2008 to July 2008. From Table 2.6, we know that there are still more 13% mobile phone not supporting mobile browsers even if Japan is one of most advanced countries on communications in the world.

Table 2.6 Mobile Telephone in Japan

Date	Total	Web	Not Web	Rate
2008.7	103,648,400	89,277,000	14,371,400	13.87%↑
2008.6	103,345,600	89,142,600	14,203,000	13.74%↑
2008.5	102,987,200	88,973,800	14,013,400	13.61%
2008.4	102,724,500	88,686,100	14,038,400	13.67%

*Although Japan has most advanced communications technology in the world, more 13% mobile phones do still not support mobile browser. In addition, even if the phone supports browsers, their capabilities are still different (*Goda, Kogure, Shimoyama, Kimura and Obari, 2008*).*

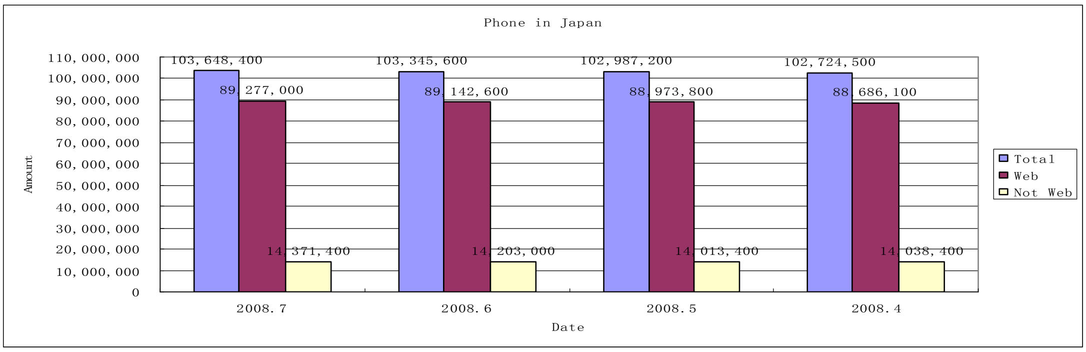


Fig.2.2 Mobile Telephone in Japan

2.4.2 Diversity of Mobile Context

AMF Ventures find that on TV only 1% of audience data is captured; on the internet about 10% of audience data is collected; but on mobile 90% of audience information can be identified (TANA, 2008), which may include Personal Context (User's preferences, calm behavior…), Social Networks (personal history, friends, blogs, …), or other Context (educational strategy, location, time, presence and related status, handset status and capabilities.) (Vitor and Maria, 2009). Considering learning context means that for educational aim we know more exact composition of learners, individually and exactly.

2.4.3 Diversity of e-Learning Contents Media

Most of e-learning contents, designed for desktop computers and high-speed network connections, are not suitable for handheld devices, whose capabilities are usually limited in terms of network bandwidth, processing power, storage capability, markup language, and screen sizes, etc(He, Gao, Hao, Yen and Bastani, 2007; Chang, 2008; Yang, 2007; Lum and Lau, 2003; Xu, Zhu, Zhang and Gu, 2008).

In general, we call the process content adaptation, which is the action of transforming content to adapt to device capabilities. Content adaptation is usually related to mobile devices that require special handling because of their limited computational power, small screen size and constrained keyboard functionality.

2.5 Parallel Production System (PPS)

A production system has three main components: productions, working memory, and an interpreter (Charles, 1982; Frank, 1986). A production is a set of If-Then statements. Each production has a name, LHS (left hand side/antecedent/condition) and RHS (right hand side/consequent/action). The data operated on the production is stored in a data set called working memory. The Working Memory (WM) is a collection of data objects that represents the current state of the system. The initial state of the working memory is defined by the user, and is modified using a production's RHS operators. Data objects are asserted into the working memory using an assert operator, and are retracted from the working memory using a retract operator. The interpreter executes a production system by performing the following operations (Charles, 1982):

(1) Match. Evaluate the LHSs of the productions to determine which are satisfied given the current contents of working memory
(2) Conflict resolution. Select one production with a satisfied LHS; if no productions have satisfied LHSs, halt the interpreter.
(3) Act. Perform the actions in the RHS of the selected production.
(4) Goto 1.

Frank (1986) describes a production system's recognize-act cycle in details. The interpreter must first match the contents of the working memory to each rule's LHS. The interpreter creates the conflict set (<Production, List of elements matched by its LHS>) by finding all of the productions that have become instantiated from the current working memory. Once all of the matching has been done, and a conflict set created, the interpreter uses the conflict resolution algorithm to determine the set of instantiations that it will fire. Once these instantiations have been fired, the interpreter repeats the cycle. System execution terminates when the conflict set is empty after the match phase. This is true because only the RHS of an instantiated production can modify the working memory.

Since execution speed has always been a major issue for production systems, several researchers have worked on the problem of efficiency. In this research, pattern matching algorithm was derived from the Rete Algorithm proposed by Charles (1982). The Rete match algorithm is an algorithm for computing the conflict set. That is, it is an algorithm to compare a set of LHSs to a set of elements in order to discover all the instantiations. The Rete matching algorithm will only once match a pattern condition to a data object for the entire life-span of the data object. A data object is compared to every pattern only when it is first placed in the working memory. This is accomplished by saving previous match information in a logical net that represents the LHS of the rule. It does not iterate over the sets because the pattern matcher can avoid iterating over the elements in working memory and production memory by storing information between cycles.

When an element enters working memory, the interpreter finds all the patterns that match it and adds it to their lists. On the contrary, the interpreter deletes the element from the lists when an element leaves the working memory.

Since pattern matches using the Rete algorithm save this kind of information, they never have to examine working memory. It may be looked as a black box model. For example, the black box might be told that the element *(Goal ?Type Simplify ?ObjectExpr19)* has been added to working memory, and it might respond that production has just become instantiated.

(Changes to Working Memory)

↓

Black Box

↓

(Changes to the Conflict Set)

Another, in order to avoid iterating over the set of productions, a tress-structured sorting network or index for the production is used. The root node is where all objects enter the network. From there, it immediately goes to the ObjectTypeNode. The purpose of the ObjectTypeNode is to make sure the engine doesn't do more work than it needs to. For example, say we have 2 objects: Account and Order. If the rule engine tried to evaluate every single node against every object, it would waste a lot of cycles. To make things efficient, the engine should only pass the object to the nodes that match the object type. The easiest way to do this is to create an ObjectTypeNode and have all 1-input and 2-input nodes descended from it. This way, if an application asserts a new account, it won't propagate to the nodes for the Order object. E.g., Fig.2.3 shows a simple Rete Network for PC and ubiquitous device.

Usually, the Rete methods creates a Rete Net for different data from working memory. Based on each state in net, the system may choose a cheapest action to complete the task. E.g. the system may choose suitable contents according to device used by users.

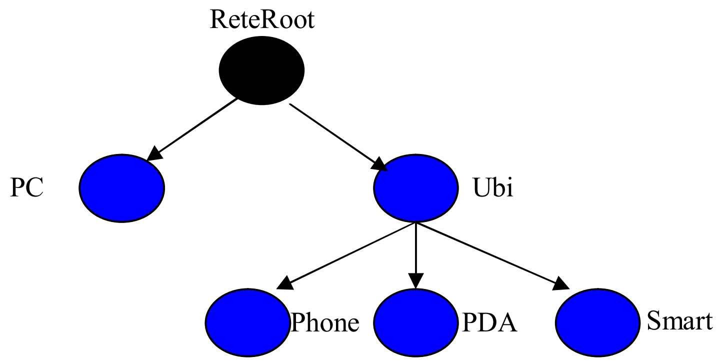


Fig.2.3 Rete Net for Ubiquitous Device

2.6 General Architecture of Content Adaptation

Content adaptation could roughly be divided into two fields: Media content adaptation that adapts media files and browsing content adaptation that adapts Web site to mobile devices. On May 2007, OMA (2007a) has released an approved version of Standard Transcoding Interface (STI 2007) for ubiquitous environments for content transcoding. Today many mobile applications are developed based on STI2007.

OMA 2007 STI has standardized the architecture model for general multimedia adaptation. STI is based on a request-response model. An STI transcoding operation is shown in Fig.2.4 [OMA, 2007 (a)], which provides a high level overview of the interaction between an application and a transcoding platform. The communication between application platform and transcoding platform is always a request followed a response. The application platform and transcoding platform may be installed at same or different server.

The transcoding requests and responses will be based on transcoding operations between the Application Platform and the Transcoding Platform. The Transcoding Platform receives the request, parses it, handles it and generates a response to the originating Application Platform.

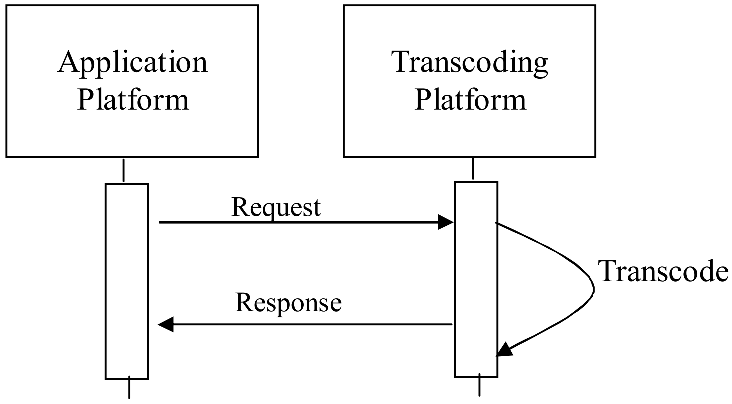


Fig.2.4 Transcoding Operation Model (OMA-STI, 2007)

2.6.1 Adaptation Strategies

For content adaptation, adaptation strategies existing are categorized: One Size Fits All, Minor Adaptation, Redirection and Unified (MOBI, 2009).

A One-Size-Fits-All

The system is designed for all users, e.g. e-Learning system, not only for pc learner, also for mobile device learner. All learners get same interface or same contents without regard to the device capabilities used at the client. The learner can not get a best experience during learning.

B Minor Adaptation

Contrast to one-size-fits-all systems, the minor adaptation system, detecting device capabilities, resizes simple contents into adaptive contents, e.g. resizing a big image into a thumbnail image in Berhe, Brunie and Pierson (2005) or deleting image or video from e-learning contents in Kojiri, Tanaka and Watanabe (2007).

C Redirection

The system builds a separate mobile site for each mobile device and redirects the separate system to learners. For example, the server provides different url to learners: http://www.example.com for e-Learning and http://u.example.com for u-Learning. That means that the LMS system should create all versions for all devices. In fact, it is not possible to realize.

D Unified

This approach needs more planning and expertise than others do. It can recode the original contents into adaptive contents for learners according to capabilities of mobile device. It can ultimately lead more satisfactory with learner experiences.

According to the time when these different content variants are created, adaptive content delivery can be classified into two main types: static adaptation (*strategy* A and C) and dynamic adaptation (*strategy* B and D) (Rho, Cho and Hwang, 2005).

In static adaptation, the server analyzes the learning context and returns the best alternative version from different pre-adapted contents (Chang, Hung, Wang, Weng, Shin and Lee, 2008), or filters the original contents (Kojiri, Tanaka and Watanabe, 2007). With static adaptation approach, content provider can have a tight control over what is transcoded and how the result is presented.

In dynamic adaptation, the desired contents are adapted and delivered on the fly according to dynamical requests from the learner. The requirements are based on the current characteristics of the learning context and learning strategy or needs (Lum and Lau, 2003; Sharples, 2007).

2.6.2 Classification of Unified Content Adaptation

There is quite a wide spectrum of implementation models for content adaptation. It's also possible for adaptation to take place in the network, and operators frequently do some adaptation between your Web site and the device. In regarding to the location where the adaptation is performed, W3C-MWBP (2008) categorizes three types of content adaptation: client side adaptation, proxy side adaptation and server side adaptation. In this research, the server side adaptation is adopted to create adaptive contents in unified adaptation strategy for learners in ubiquitous learning environment.

A Client Side Adaptation

Client side adaptation supposes that the client, device, can make a decision to create adaptive contents according to device features. For example, client side adaptation usually relies on using the media selectors associated with CSS. Style sheets can provide a different experience for the same page on mobile device.

Table 2.7 CSS Example for Client Adaptation

```
<head>
  <meta http-equiv="Content-Type"
content="application/xhtml+xml; charset=utf-8"/>
  <link href="pc.css" rel="stylesheet" type="text/css" />
  <link href="mobile.css" rel="stylesheet" type="text/css"
media="handheld" />
</head>
```

Client-side adaptation has its drawbacks. It needs additional network bandwidth (Adriana, Lon and Marian, 2008). Also not all browsers support the CSS media types, and simply relying on this method may render some pages broken in certain devices. The users will suffer the delay and cost of doing this. It is not recommendable to realize the adaptation at the final learner because the transcoding possibilities of the client side approach is very limited due to the lack of computing power and bandwidth.

B Proxy Side Adaptation

Proxy side adaptation is where the content is altered as it passes through one or more network components. It is a transparent adaptation method, e.g. google transcoder. Some network operators, for example, compress images before they are passed over the air to the mobile device. Usually, the proxy does not know more features of contents or user's preferences, low-level adaptation can be applied for data codification format.

It is difficult for both methods to create adaptive contents based on learner's preference or need because they know few users' preference.

C Server Side Adaptation

Server side approach supposes to realize the contents adaptation at the server level. It should create adaptive contents based on learning experience. First, the server should create adapted contents based on device capabilities. Of course, the system should also compute the learner's preference. At last, the server determines the suitable markup language for ubiquitous device. One example code in PHP for markup language adaptation is shown in Table 2.8.

The device capabilities are most important among all learning context. This can be achieved by interpreting the User Agent information in the HTTP headers that the browser sends to the server.

Table 2.8 Adaptive Header Information for Server Side Adaptation

```
<?php
if($device =='wml'){
    header("Content-type: text/vnd.wap.wml");
    echo '<?xml version="1.0"?>';
}
else {
    header ("Content-Type: application/xhtml+xml ");
    echo '<?xml version="1.0" encoding="utf-8"?>';
}
?>
```

Server side approach is able to overcome the problems that the client/proxy side approach has. After a web server employs some type of device detection together with a device feature repository, the server sends optimized content tailored for the particular device, and only the necessary amount of data is transferred in the network.

2.7 Reviews of Literature

The ability of transcoding the content according to the device capability and learner's preference and experience is regarded as context awareness, which includes three important aspects of context: (1) where you are; (2) who you are with; and (3) what resources are nearby (Hsiao, Hung and Chen, 2008). Next, the mobile device profiles & methods existing for adaptive contents are reviewed in brief.

2.7.1 Device Profile

Ubiquitous mobile devices usually differ in hardware, software, and browsing capabilities. Capabilities of ubiquitous devices can be achieved for each learner based on device preferences profile describing the capabilities after the adaptation system receives http request from mobile device.

Today there are two main preferences profile recommendation model for mobile device. Composite capabilities/preferences profile (CC/PP) and User Agent Profile (UAProfile), developed by W3C-CC/PP (2004) and OMA (2007b) separately, are the prevalent standards of describing the device capability. The specifications of CC/PP and UAProfile follow the standard of resource description framework (RDF), which is based on XML and has a tree structure to record the value of each feature (W3C-RDF, 2004).

There are millions of mobile devices existing today. In general, these device profiles are stored on the server of device manufacture. Also, it is growing everyday. So the system developers have to collect each profile from these device manufactures for applications. Fortunately, Luca has defined a Wireless Universal Resource File (WURFL) model to describe the features of mobile devices (WURFL, 2007). WURFL model is an XML configuration file which contains information about capabilities and features of many mobile devices in the wireless world. Also, the repository of device in WURFL is updated everyday by contributors in the world. In terms of adoption, WURFL is today more popular than pure UAProf or CC/PP solutions. Of course, there are some business models based on WURFL model today, e.g. Deviceatlas (2007).

2.7.2 Review on Existing Techniques

Some researchers have extended the existing e-Learning system to portable device. Chang, Hung, Wang, Weng, Shih and Lee (2008) design some templates to make e-Learning objects adapt to different handhelds, which can reduce the workload of LMS managers. Farooq, Schafer, Rosson and Carroll (2002) have extended an existing personal computer based on online learning community to ubiquitous devices to allow students participating in ubiquitous learning. Learners can also chat with their peers or interact with the content server by sending message in SMS. Similar m-Learning systems, Bollen, Eimler and Hoppe (2004) and Scornavacca, Huff and Marshall (2007), also allow students to participate in discussion by SMS/MMS. Participants may send text message, image, or animation to share experiences during learning. These supplement e-Learning environment with new data services, such as instant chat, event alters and other campus services. These improve collaboration among learners for literature course.

Besides SMS, Motiwalla (2007) allows learners to access some rich contents by browser-based push and pull technology and enriches the student's learning. Learners may interact with others by browser directly. To rich learning objects, Kojiri, Tanaka and Watanabe (2007) use simple filtering technology to remove rich contents (e.g. image, video) to provide adaptive contents. Patel, Agarwal, Rajput, Nanavati, Dave and Parikh (2009) develop a prototype system to help farmers to learn agricultural knowledge through the speech and dialed input voice interface on mobile phone in developing countries. Farmers can get guidance from specialist at any time and any place by speech.

Furthermore, Ariel, Shriram and Michael (2003) and Timo and Tapio (2005) propose adaptation content algorithms to parse the HTML contents for mobile users. He, Gao, Hao, Yen and Bastani (2007) propose an extensible content adaptation system, Xadaptor, which can classify HTML page objects into structure, content and pointer objects. Xadaptor adapts Web pages for mobile devices using a rule-based approach. Rules are matched to client profile to provide flexible content adaptation for clients with diverse hardware and software capabilities and user preferences. It is easily extensible for supporting new contents types.

Lum and Lau (2003) develop PDF Document Content Adaptation System (PDCAS), which is aware of the user context in five quality domains: color, transmission time, scaling, modality, and segment. The user can view PDF file on mobile device by image, html, WML satisfactorily. Ero, Berkner and Joshi (2008) propose a novel visualization for documents, called Multimedia Thumbnails, which consists of text and image contents converted into playable multimedia clips. Xavier, Beltran, Casademont and Catalan (2008) propose a ubiquitous web access model to negotiate content in order to obtain adapted contents according to device capabilities.

Bryan, Inmaculada and Brendan (2006) use educational activity, networks, learning state, etc. to identify the interest & preference of learners and create adaptive contents for learners in a ubiquitous environment. Network speed has also been considered in Xavier, Beltran, Casademont and Catalan (2008) and Hsiao, Hung and Chen (2008). Some similar researches use one or more contexts, for example, learner's state, educational activity, infrastructure's state, environment state used in Economides (2006), the location, identity, time, and activity in Schilit, Theimer and Welch (1993), physical and social environment, device state, cognitive, behavior and task in Schmidt, Beigl and Gellersen (1999), to create adaptive learning. When a LMS server employs user's experience with the context awareness, it can then send optimized content to the requesting device.

In order to keep the characteristic of contents, Rho, Cho and Hwang (2005) and Shaha, Desai and Parashar (2001) present a QoS aware adaptation scheme of multimedia contents to reduce the bandwidth required for delivery. They can adapt multimedia contents in accordance with learner, system and network state to meet end-to-end requirements. Some studies, e.g. Lum and Lau (2003) and Li, Feng, Li, Gu, Lu and Chen (2006), have also adopted caching strategy to reduce the transcoding time. When caching content stratifies with transcoding requirement, the server returns the cached contents directly.

2.8 Summary

This chapter mainly discusses the research background about adaptive content delivery. First, the formal and informal educations are introduced. Then, the difference between adaptive e-Learning and u-Learning are compared. Thirdly, the PPS methods are explained. Fourthly, the architecture, methods, and strategy of content adaptation are explained briefly. Lastly, profile models of ubiquitous device & state of literature are discussed.

Next chapter will introduce the architecture of adaptation system for adaptive content delivery proposed in this thesis.

Chapter 3

Three Level Service Models

Objectives

This chapter explains:

- Ubiquitous Learning Environment
- Three Level Service Models
- System Architecture
- Special Features of Architecture

Overview

This chapter mainly explains working mechanism of adaptation architecture in ubiquitous learning environment. First, the concepts & feature of context data are discussed. Also, learning context in ubiquitous environment is also defined. Secondly, the three level service models are proposed: content service, transcoding service, and presentation service. Thirdly, the system architecture of adaptive content delivery is introduced according to three level service models. Also, the working mechanism of content delivery is explained briefly. At last, the special features of this research compared with general system are also discussed.

3.1 Introduction

Location is one aspect of the physical environment, and as evident from currently reported work location is often used as an approximation of a more complex context (Albrecht, 1999). While the computer science community has initially perceived the context as a matter of user location, as Dey (2001) discuss, in the last few years this notion has been considered not simply as a state, but part of a process in which users are involved; thus, sophisticated and general context models have been proposed to support context-aware applications (Cristiana, Carlo, Elisa, Fabio and Letizia, 2007; Albrecht, 1999).

Recent applications have a stronger educational underpinning attempting to engage learners with their surroundings and to make them explore their environment through touch, sight and sound (Patten, Sa´nchez and Tangney, 2006). Context and context-awareness began to be investigated in distributed computing with emergence of mobile computing components in the beginning of the 90s, led by the desire to support computer usage adequately in varying physical environments (Albrecht, Michael and Gellersen, 1999). Dey (2001) define context as "Any information that can be used to characterize the situation of an entity, where an entity is a person, place, or object that is considered relevant to the interaction between a user and its application, including the user and the application themselves. Context is typically the location, identity and state of people, groups and computational and physical objects." By the use of sensors and positioning data collected, these applications attempt to allow learners to engage with, and be engaged by, their context. The contextual approach supports several learning methodologies ranging from those instructional in nature to more constructivist ones (Patten, Sa´nchez and Tangney, 2006).

Another, the contents from Learning Management System (LMS) are designed for pc in general. The contents adaptive to learning environment can not be displayed correctly on ubiquitous device or may not be suitable to network characteristics. So the recommended contents should be recoded before they are sent to learners.

The combination of location aware technologies and a contextual learning approach facilities learners to construct meaningful contextualization of concepts during field trips (Michie, 1998; Patten, Sa´nchez and Tangney, 2006). So in u-Learning, we may provide contents not adaptive to learners, but adaptive to learning environment.

3.2 Adaptive Content Delivery for u-Learning

Context awareness originated as a term from ubiquitous computing or as so-called pervasive computing which sought to deal with linking changes in the environment with computer systems, which are otherwise static. A rich mobile user experience leverages mobile context. In computer science, it refers to the idea that computers can both sense, and react based on their environment. Mobile devices may have information about the circumstances under which they are able to operate and based on rules, or an intelligent stimulus, react accordingly. Successful mobile applications are the ones that are great at delivering a great mobile user experience (Ortiz, 2008). One of the most crucial considerations in content provision for e-Learning system is that learners have different information needs depending on their current context (Xu, Zhu, Zhang and Gu, 2008). The learner's needs are much more varied from one state to another state.

3.2.1 Benefits of Mobile Context

The users use mobile device to access an object at any time & place and to connect with any body in a real world. The application uses current circumstances to provide adaptive contents for users. Different application may use different context data to compute. Fig.3.1 gives the most elements in general. Among all contexts, social context are most important elements for applications, which may conclude social information (calendar, who stay with...), action, et al.

The most significant feature of mobile technology is the mobility per second (Niina, Matti, Virpi and Anssi, 2009). Mobile computing provides users with more freedom, as they can access information and services without having to find a physical space, such as, an office or an Internet cafe for Internet connection (May, 2001). Kleinrock (1996) labels the benefits provided by mobile technologies as "anytime and anywhere computing" and outlined the two most common dimensions of mobility – independence of time and place.

Mobile Context may be any resource available by users, such as location, device, presence, even the temperature and noise around him/her.

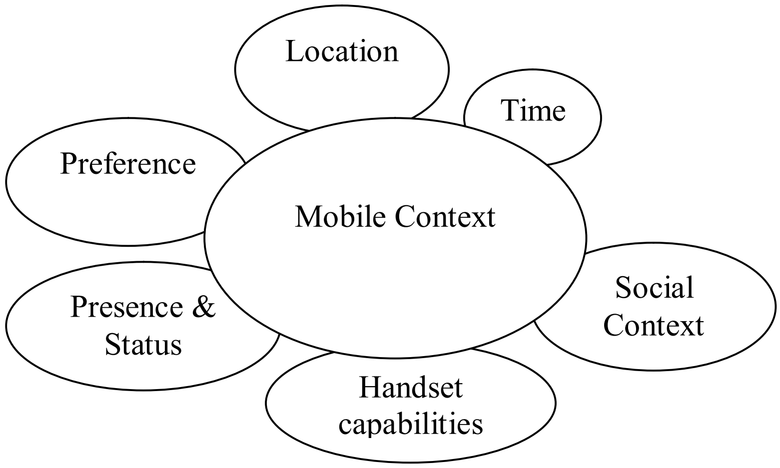


Fig. 3.1 Elements of Mobile Context (Ortiz, 2008; Peter, 2001; Vitor, et al, 2009)

Mobility is not just a matter of people moving but, far more importantly, related to the way in which they interact with each other in their social lives. Kakihara and Sørensen (2001) expand the concept of mobility into three dimensions of human interaction: spatial, temporal and contextual mobility. The spatial and temporal dimensions correspond to those of Kleinrock's anytime and anywhere computing (Kleinrock, 1996), whereas the contextual dimension extends the definition further. Modern technologies allow people to work in a flexible and independent environment from geographical and temporal constraints. Contexts in which people reside continuously frame their interaction with others, including people's cultural background, particular situation or mood, and degree of mutual recognition (Kakihara and Sørensen, 2001).

Usually, we call human interaction as social context, which are the identical or similar social positions and social roles as a whole that influence the individuals of a group. Leveraging the mobile context has a positive effect on the mobile user experience, such as informative, timely, useful, connected, dynamic, adaptive (Ortiz, 2008).

3.2.2 Ubiquitous Learning Environment (ULE)

The ubiquitous learning environment provides an interoperable, pervasive, and seamless learning architecture to connect, integrate, and share three major dimensions of learning resources: learning collaborators, learning contents, and learning services (Chang and Sheu, 2002; Cheng, Shengguo, Kansen Huang and Aiguo, 2005; Haruo, Kiyoharu, Yasufumi and Shiho, 2003; Yang, 2006). Ubiquitous learning is characterized by providing intuitive ways for identifying right contents and right services in the right place at the right time based on learners surrounding context such as where and when the learners are (time and space), what the learning resources and services available for the learners, and who are the learning collaborators that match the learners' preferences (Ogata and Yano, 2004; Yang, 2006). The adapted contents can be best matched to the learner's preference under current context (Lum and Lau, 2003).

As a result, the effectiveness and efficiency of ubiquitous learning heavily relies on the surrounding context of learners (Yang, 2006). Economides (2006) proposes adaptation engine in an adaptive mobile system that uses learning automata to implement the probabilistic adaptation decisions. The Learner's state, educational activity's state, infrastructure's state, and environment state are considered into context as input to adaptation learning system.

In general, the context data may be from learner, learning environment, or educational strategy and so on. The context data in ULE are usually followed into four categories: device capabilities (DC), network characteristics (NC), learning environment (LE), and learner characteristics (LC), which is shown in Fig.3.2.

DC: Codec capabilities; Input-Output capabilities; Device features
NC: Network features (static features);Network conditions (dynamical features)
LC: Learner Information and learning process; Presentation preferences
LE: Location; Time; Social awareness

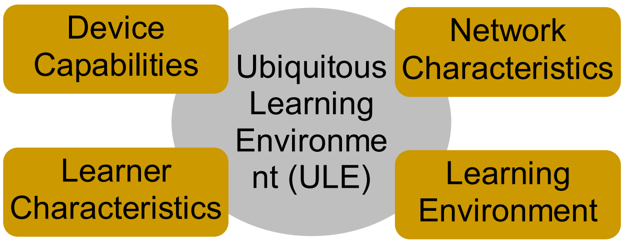


Fig. 3.2 Categories of Context in ULE (Vitor and Maria, 2009)

Ubiquitous learning contexts (DC, NC, LC, and LE) in this research are categorized into two aspects: contextual data and situational data. Contextual data are from client side: the learning time & place, device feature and learning history. Situational data are from server side: learning preference, device capabilities, network features. The adaptive content O' is ranked by $P(O \to O' | L, E)$. The $U_i(t)$ is used to define the ubiquitous learning state at time t for learner i:

$U_i(t) = [L_i(t), O_i(t), E_i(t)]$ --Formura 3-1

where:

$L_i(t)$: learner's (L) preference at time t

$O_i(t)$: items state in learning object (O) at time t

$E_i(t)$: contextual learning environment (E) at time t.

In learning experiment environment, we mainly consider the location, time, and network performance, network type, and device type as learning context awareness. The definition is

$E_i=(l_i, t_i, u_i, d_i, p_i, m_i)$;

l_i: location (home, train, road, classroom);

t_i: time;

u_i: upload speed by mobile device;

d_i: download speed by mobile device;

p_i: network type (GSM, 3G, IEEE802);

m_i: mobile device type (PC, PDA, Smartphone, Mobile Phone)

For example: such as a learner access learning content by his GSM phone in the moving car at 10:30. The E_i =(car, 10:30, 6, 24, GSM, Phone).

3.3 Three Level Service Models

The Mars Medical Assistant (MMA) (Luis and Frank, 2000) uses a combination of user model, task model, and situational model to resolve the conflicts according to the semantic content and cognitive characteristics of component's media type. Finally, the virtual hypertext structures as adaptive contents are created based on rule mechanisms.

The adaptive process in this research is completed through the following three-steps: adaptive to context, content adaptation and content delivery. The adaptive process to context creates suitable content for learners according to contextual data and situational data. Secondly, content adaptation process recodes original content into adapted contents according to the adaptive suggestion, from adaptive process. According to the discussion above, the adaptive content delivery model proposed is shown in Fig.3.3, which is refined according to the research model (Fig.1.2).

Adaptive process is made of three-steps: adaptive to learning context, content adaptation, and adaptive content delivery. The three-steps complete adaptive process together. The adaptive learning model recommends the adaptive contents according learning situation and context. Then content adaptation model creates adaptive content based on learning environment. At last, the content delivery model delivers adapted content embedded with suitable markup.

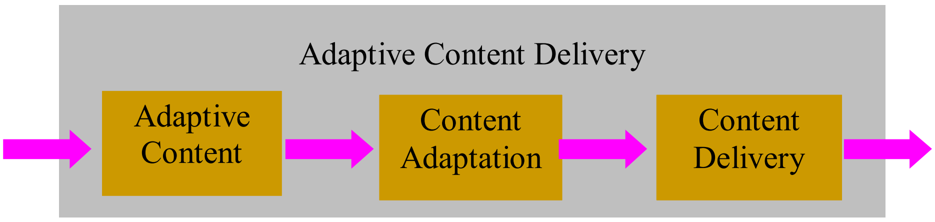


Fig. 3.3 Model for Adaptive Content Delivery

During each step, there are many conflictions existing. In general, the confliction will be resolved by rule base according to PPS system. According to adaptive model proposed in Fig.3.3, the interaction operations proposed in this research are shown among three level services, which are instantiated by the content service, transcoding service, and presentation service in Fig.3.4.

When learner learns with his ubiquitous device, the system will distribute suitable content for learners.

1. *Content service suggests the suitable content according to learning context & situation;*
2. *Transcoding service recodes adapted contents according to transcoding suggestion;*
3. *Presentation service adopts suitable format for learners at last.*

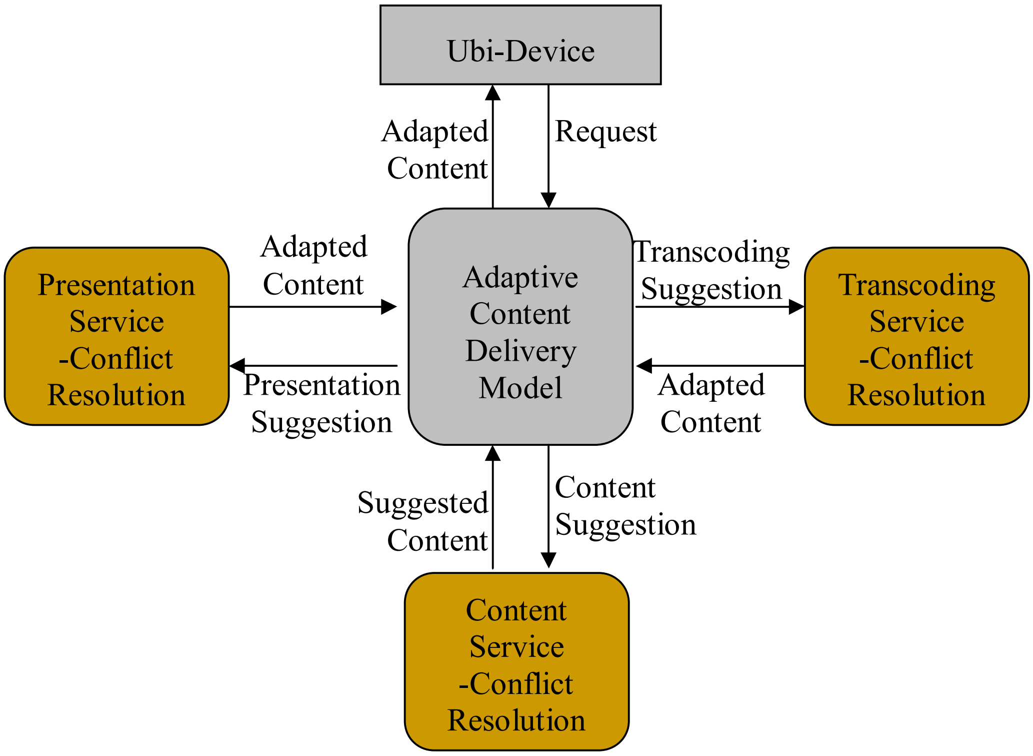


Fig. 3.4 Three Level Service Models

- The content service suggests what information is recommended, specially learning contents under current contextual (dynamical and static) environment based on content suggestion. These are computed by adaptive learning model in Fig.3.3.

- The transcoding service recodes or reconstructs the suggested contents into adapted contents according to transcoding suggestion, which is generally produced based on learning context (device, network, etc.).. Transcoding services use many transcoding agents to complete the transcoding tasks by one or more steps, e.g. when learners study in courseware on cell phone, standard document transcoders transform courseware file into text, audio transcoders transform text into speech or other transcoders transform them into other media.
- The presentation service determines the final adaptive content format according to presentation suggestion, which is determined according to learning environment. At last, the adaptive contents are distributed to learners.

The conflicts among three services are resolved by rule bases. The suggestion references and conflict resolutions are rule-based mechanisms. Within each service, the conflicts can occur due to differences in suggestions from adaptive content delivery model. For example, the learner is accessing a learning object based on text while riding his bicycle. The adaptive content delivery model suggests audio as media type for learning. At last, the presentation service determines what pattern of learning content is provided for learners, e.g. mobile page, file, or message.

3.4 Proposed System Architecture

According to the three level service models proposed, this section proposes adaptive content delivery architecture for ubiquitous learning environment, which contains four core components: Adaptation Model, Context Reasoning Model, Transcoding Model, and Delivery Model, which are shown in Fig.3.5. Two negotiation module are used to resolve the conflicts in content services, which are contextual module and situational model in Adaptation Model.

First, context data, for example, device capabilities by device module based on http request headers (partial context awareness from mobile device) and device/browser repository, location by GPS, are sensed or detected. The device detection algorithms are explained in details in chapter 4.

The four Models (Context reason model, Adaptation Model, transcoding model, and delivery model) constitute the system architecture in this research.

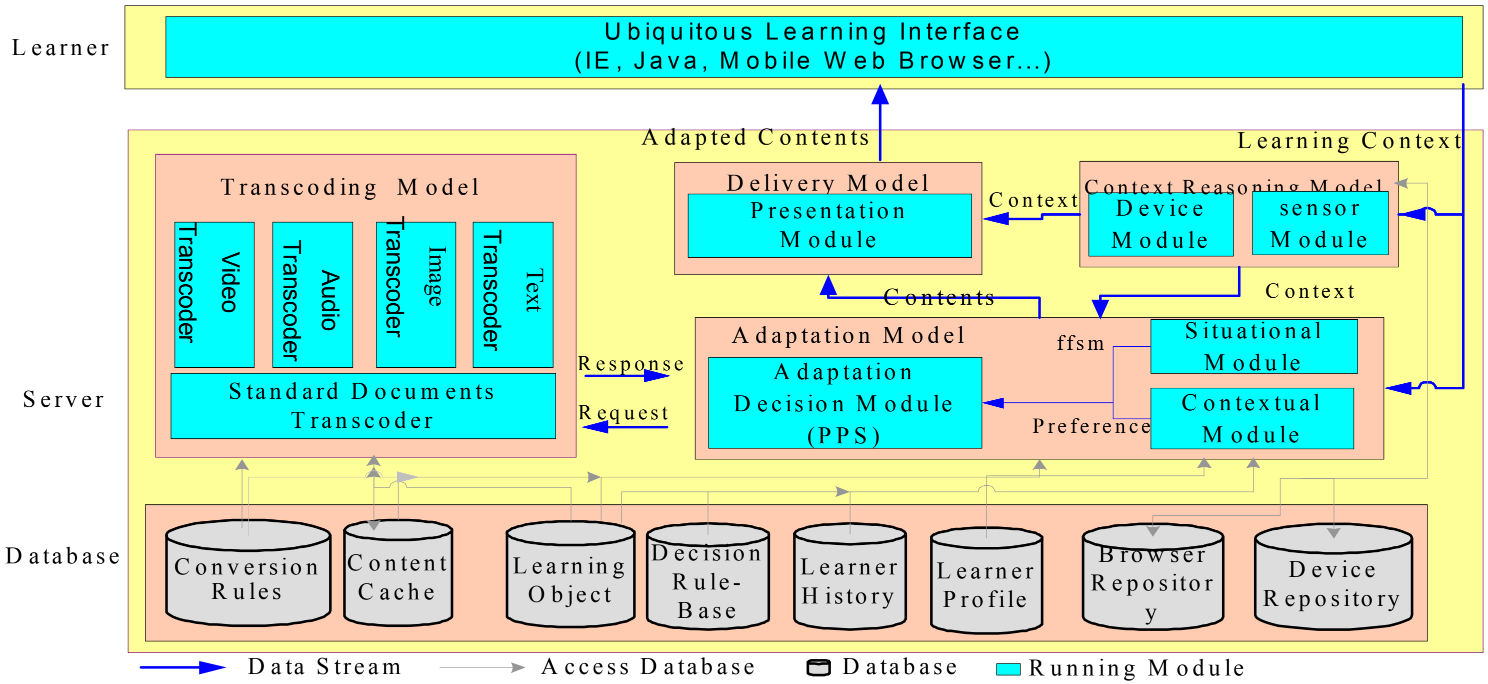


Fig. 3.5 System Architecture for Adaptive Content Delivery

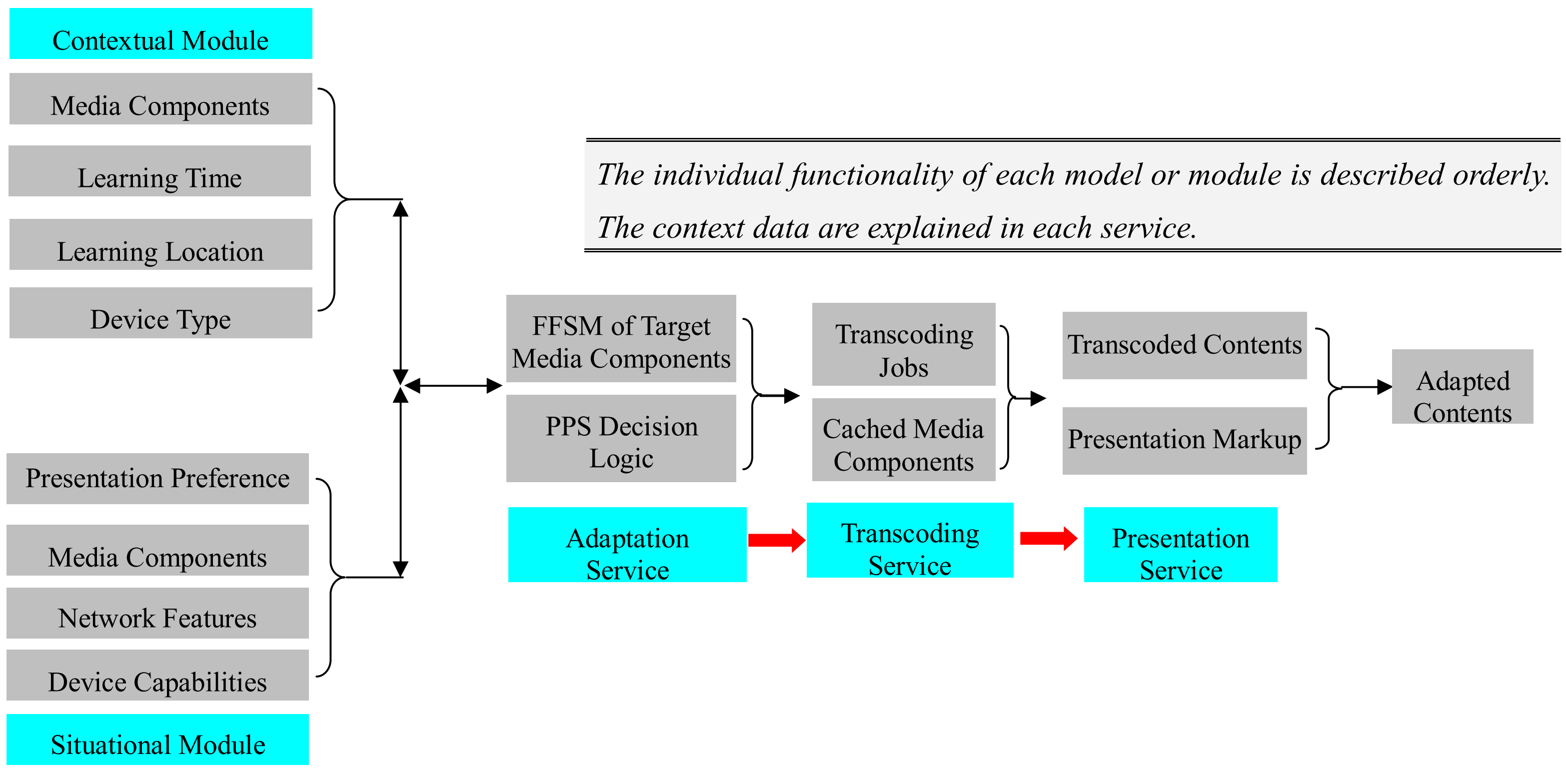


Fig. 3.6 Contextual Data Flow Diagram for Adaptive Content Delivery

Secondly, contextual module recommends adaptive contents for learners by the ubiquitous learning state $U_i(t)$. After analyzing learning experience under current context awareness (learning media component, learning time, learning location, and device type), the preferred media type is recommended.

Thirdly, situational module in Adaptation Model negotiates the contents based on device capabilities, network characteristics (context awareness), learning media component, and learning preference and creates a feature finite state machine for learning media component accessing.

Fourthly, the adaptation decision module determines the transcoding jobs under the decision logic condition according to feature finite state machine created by situational module. Then, a transcoding request will be sent to transcoding model, which transcodes media into adaptive content based on constrained version of contents.

Lastly, presentation module sends adapted contents to learner by embedding suitable markup language (HTML, WML, XHTML MP or cHTML) or by SMS, MMS after delivery model gets the transcoding results from Adaptation Model.

According to the contextual and situational data considered in this research, the Fig.3.6 describes the context data flow used in different step. Among them, the contextual module, situational module, adaptation decision module, and transcoding model are the focus of the research. Each model or module resolves the confliction under different service level by different negotiation method. The realization details will be discussed in chapter 4 & 5.

For example, contents of text and image will be recommended when the learner is staying at a noise station. On the contrary, the audio content (should delete texts and images from original content) will be provided while the learner is walking. Of course, the playing time of audio should be considered according to his available learning time.

When the format of image or audio is not supported by mobile device, transcoding model recodes the content by the request suggestion from situational module, such as format conversion of image from jpg to gif.

3.5 Special Feature of Proposed Methods

The adaptation process is based on three level services proposed in thesis. Each service uses different negotiation method to resolve the confliction. According to the discussion above, there are much special features about this research.

First, closest capabilities detected by new methods. In general, the system detects the device capabilities based on the user agent from http request headers. This research uses all header information to detect the device features for application. The research can also recommend device capabilities for device even that there is no device bank in system. Another, the device/browser banks are updating dynamically according to device profiles.

Secondly, contents adapted to learning situation and context. In general, the mobile application system provides adapted contents according to device capabilities. In this research, according to PPS system, the contextual and situational modules create adaptive contents according to learning context-aware. The state space will be reduced because of cross-use of state.

Thirdly, low response time for content transcoding. The transcoding in the sky will take more time. This research proposes a new caching method, which is based on FFSM model, which can reduce the transcoding response time during request. Also, it needs low computing resource during transcoding.

Fourthly, expandability. The proposed method is not an isolated component. It is easy to apply the proposed method into different e-Learning system. Another, the proposed architecture are not applied on education, also other fields, e.g. video/audio sharing, document viewing and so on.

3.6 Summary

This chapter mainly explains the proposed architecture for adaptive content delivery in ubiquitous environments. According to the definition of context awareness, the ubiquitous learning environment is given. Then, the three level service model is proposed. Followed it, the system architecture is explained. Also, the functionalities and data flows of four core components for adaptive contents are explained briefly. Finally, the special features of this research are discussed.

Next chapter will introduce two methods about the device detection mechanism in ubiquitous environment. Also, one of service, presentation service, will be also explained.

Chapter 4

Device Detection & Presentation Service

Objectives

This chapter explains:

- Formal Definition
- Device Detection Mechanism
- Delivery Mechanism

Overview

This chapter explains the technology contribution to device detection & presentation service in this thesis. First, the related terms and concepts used in this research are defined. Then, the detection algorithms for device capabilities in context reasoning model are explained in details. Thereafter, the delivery mechanism is discussed based on adapted mobile page, mms or mobile mails for learners. An example in mobile pages is demonstrated at last.

4.1 Introduction

Due to the fact that these mobile devices are taken with the user at any time, large amounts of context information detected can be used to learn about the learners' behavior and wishes in a given context (Przybilski, 2005). One of the main challenges in future learning system is to provide intelligent and context-aware contents that take into account more learners' context (Nurmi and Floréen, 2004; Vitor and Maria, 2009; Yang, 2006), e.g., the data that can be used to characterize the learning situation, not just the past learning experience.

Nishikant (2005)'s research shows that the genesis of adaptive learning in e-learning system can be attributed to the development of formal theories of knowledge representation and the connectionist and symbolic approaches to learning. Under ubiquitous learning environment, the system refers them to predict the learner's future behavior after the context data are recognized (Nurmi and Floréen, 2004). According to the learner's behavior, the adaptive contents are recommended to learners (Yao and Wua, 2009; Wang, Wang and Huang, 2008).

First of all contextual data, the system should judge whether these contents are correctly played on ubiquitous device (Adriana, Ion and Marian, 2008). It is useless for learners even that the system provides the most personalized learning contents if the contents can not be displayed or played on devices correctly.

Another, the system should consider what presentation formats are provided for learners according to different learning environment. At last, the learning system pushes recoded contents to remote learners, which contents are adaptive to learner's preference, also to learner's context. For example, the best contents are provided based on audio while the learner is walking.

4.2 Formal Definition

For the sake of the formal representation to describe the approach, the formal definitions and algorithms for ubiquitous learning are introduced.

Definition 0: **Set of Object** (SO) is a feature set for a object o, $SO_o=\{f| \text{ f is a feature of object}\}$. Here, object may be context, content, learner.

For example, PDF learning object: $SO_{pdf}=\{format, size, name, \ldots\}$.

Definition 1: Set of Context Value (SC) is a value domain for a feature f of Object o, $SC_{o,f}=\{v_f| \ v_f \text{ may be continuous or discrete}, f\in SO_o\}$.

For example, learning place in u-learning system: $SC_{o,place}=\{home, walking, train, campus\}$; Learning Content size: $SC_{c,size}=[0, 100Mb]$.

Definition 2: Feature-Value (f-v) is a two-tuples, f-v = <*f*, *v*>, *v* is value of the feature $f, f \in SO_o, v \in SC_{o,f}$.

For example, When learner is learning at home, we may define the place-value of learning context, so f-v = <*place, home*>.

Definition 3: **Device Capabilities** (D) is a *f-v* set for a mobile device d,

$D = \{d_i | d_i = <f_i, v_i>, f_i \in SO_d, v_i \in SC_{df}, i \in [0,n]\}$

-Where, n total count of capabilities of device detected by Device Detector.

For example, f=amr is a sound format for mobile device, if

d=<f, 1> means that the device supports amr format of sound; else

d=<f, 0> means that the device does not supports amr format of sound.

Definition 4: **Learning Media Component** (I) of learning content is a set for a learning object o,

$I = \{i_j | i_j = <f_j, v_j>, f_i \in SO_o, v_i \in SC_{o,f}, i \in [0,n]\}$

-Where, n is the total count of features considered for learning object *I*.

For example, a pdf learning object,

I={<format, pdf>,<size, 100k>…}.

Definition 5: **Learning Content** (C) containing many learning media components, such as a web page containing text information, image, and audio sequentially: $C = \{I_i | I_i$ is a learning media component in C, $n \in [1,n]\}$

-Where, n is total count of different item in learning content.

For examle, the leraning contents in Table 4.1 is parsed into set $C=\{I_1,I_2\}$, I_1={<type,text>,…}, I_2={<type,image>,<title,java>,…}. The refined data is stored in Table 4.2.

Table 4.1 Example for an HTML Code

```
<div id="header">
Java is a programming language originally developed by  James Gosling at Sun
Microsystems and released in 1995 as a core component of Sun Microsystems'
Java platform. The language derives much  of its syntax from C and C++ but
has a simpler object model and fewer low-level facilities. Java applications are
typically compiled to bytecode (class file) that can run on any Java Virtual
Machine (JVM).
</div>
<div class="image">
<img src="http://upload.wikimedia.org/wikipedia/en/3/39/Java_logo.svg"
alt="Java" />
</div>
```

Table 4.2 XML Adaptation for HTML code

```
<item type="text">
<attribute name="text" value="Java is a programming language originally
developed by  James Gosling at Sun Microsystems and released in 1995 as a
core component of Sun Microsystems' Java platform. The language derives much
of its syntax from C and  C++ but has a simpler object model and fewer
low-level facilities. Java applications are typically compiled to bytecode (class
file) that can run on any Java Virtual Machine (JVM)."/>
</item>
<item type="image">
<attribute name="src"
value="http://upload.wikimedia.org/wikipedia/en/3/39/Java_logo.svg"/>
<attribute name="alt" vlaue="Java"/>
</item>
```

Definition 6: **Transcoding Job** (J) shall contain accessed learning contents parameters (contents feature parameters) and may also contain constrained features of accessed learning contents finally. It is used to create a transcoding action. In this research, xml file is used to store transcoding job. A transcoding request contains one or more transcoding jobs.

Definition 7: **Transcoding Result** (R) shall is composed by features of adapted contents and transcoding results. The transcoding result has similar attribute with transcoding job, which is included in a transcoding response.

Fig. 4.1 shows an overview of the request/response components. Multiple bulks transcoding within a single Transcoding Request is allowed by the proposed interface: therefore we will distinguish between Transcoding Job (individual media Transcoding) and Request Body, which can contain one or several Transcoding Jobs as part of one single request to the Transcoding Platform.

A transcoding request is an XML file, which contains one or more transcoding jobs. For this, OMA standard specification model (OMA, 2007a) is adopted. Each transcoding job contains a source and a target. The source represents input a media file (stored on local server) and its characteristics and the target represents the desired output characteristics. Corresponding to request, transcoding response is also a XML file, which contains one or more transcoding result, media location, etc.

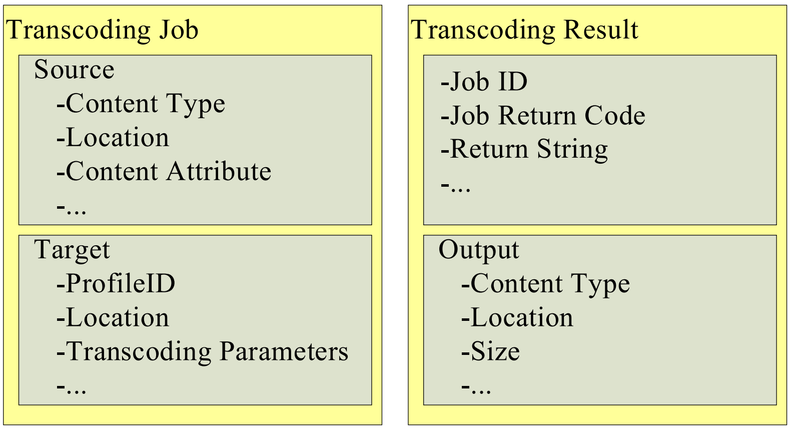


Fig.4.1 Descriptions of Job & Result (OMA, 2007a)

Corresponding to transcoding job, transcoding Response (response of the Transcoding Platform to the Transcoding Request) contains the Jobs Results (the Transcoding Jobs' results). In the response body, parameters either relate to the whole transcoding operation or the individual Transcoding Jobs' results. For example, the total duration parameter corresponds to the complete operation's duration. In the Job Results, there are parameters describing the particular Transcoding that was performed (e.g. the specific job's return code, return string, duration).

4.3 Device Detection Mechanism

The task of using context data in an intelligent way is one of the most challenging contemporary research tasks and is often referred to as context reasoning. Nurmi and Floréen (2004) show that a more precise definition for context-reasoning is deducing new and relevant information to the use of applications and users from the various sources of context data. These definitions can achieve a consistent more reliable and semantically rich description of the user context (Przybilski, Nurmi and Floréen, 2005).

4.3.1 Classification of Contextual Data

Context Reasoning Model can detect or sense the contexts from learning environment. From Fig.3.1, we know that there are four categories contexts in u-Learning. In this research, learning place and time, network speed (upload &download speed), and device type are also considered except for device capabilities, which are categorized into two groups: pre-referring context and pre-sensing context.

- **Pre-sensing context**

  The context in pre-sensing contexts are sensed or detected by some shared systems or sensors, e.g. Location by GPS, sensorMap, or u-Japan, speed of upload & download, network type. So for pre-sensing context, the data are shared from these systems.

- **Pre-referring context**

The context in pre-referring context can be sensed or detected by u-Learning system, e.g. device capabilities, device type, learning time, and so on. In this research, detection for device capabilities is explained in details.

4.3.2 Algorithms for Device Detection

Device module takes responsibility for detecting capabilities (memory, screen size …)

of the client device. The WURFL (2007) is adopted to define the profiles of devices and mobile browsers, which mainly defines the user agent based on device profile. However, as there are many different kinds of mobile devices, and new ones appear on the market on an almost daily basis, it is impossible for device module to keep an inventory of all of these devices and configurations, even for just one mobile service carrier.

The method uses all headers to recommend closest capabilities of mobile device. The process is divided into three steps: matching model, matching mobile browser and recommended features.

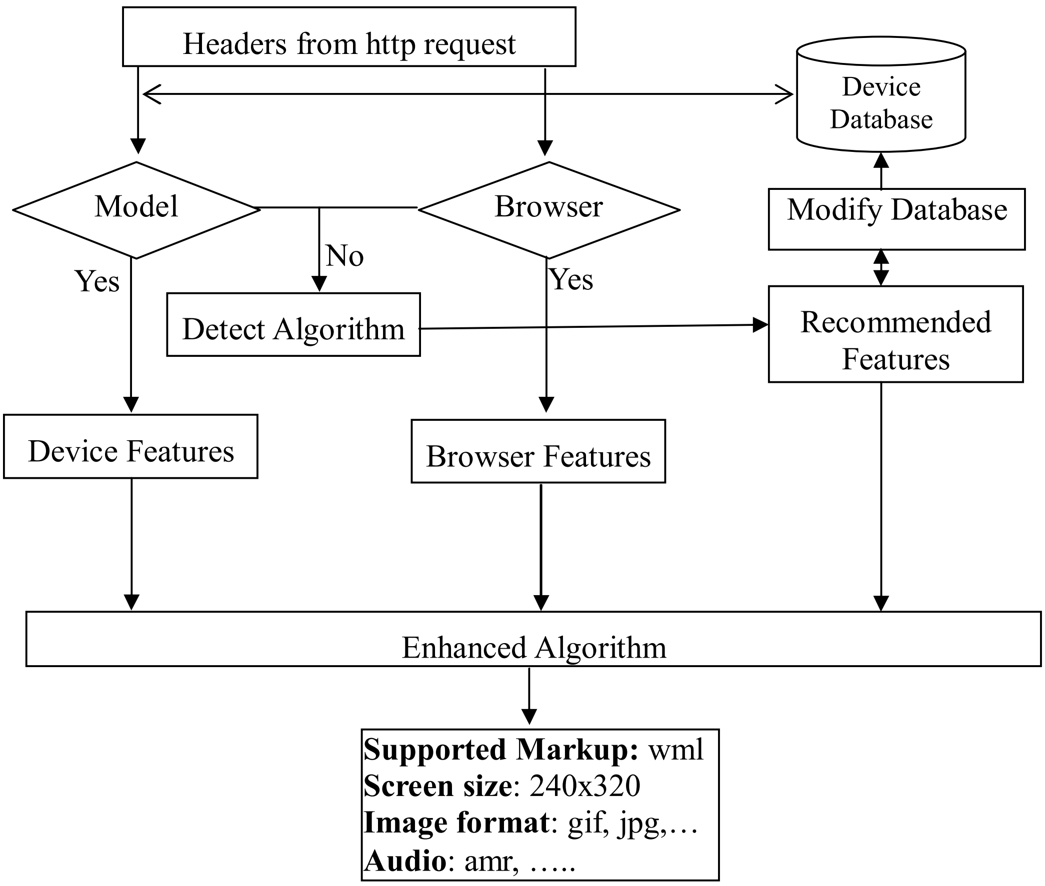


Fig.4.2 Detection Method of Mobile Device

Therefore, it is important for learning system to provide a mechanism to produce the substitute of capabilities for mobile devices in the case of detection failures of the system. The research proposes a new method to detect the feature of ubiquitous device dynamically. The method uses all headers from http request to recommend device capabilities. The flowchart is shown in Fig.4.2. This mechanism is divided into two steps:

Step I: Retrieve features from device/browser repository by matching the value in *user agent* header (Table 4.3), which is sent with the http headers from mobile device. The system adopts the algorithm of Levenshtein Distance (Paleo, 2007; WURL, 2007) to match this value to the device repository (Table 4.4).

Table 4.3 Example for User Agent From Softbank 705SH

<u>User agent:</u> *Vodafone/1.0/V705SH/SHJ001 Browser/VF-NetFro nt/3.3 Profile/MIDP-2.0 Configuration/CLDC-1.1*

Not only the features of the phone, but also the features of the device's browser are important when adapting contents. In fact, we may use the features of the browser instead of the features of the mobile device when we can not detect the mobile device, that is, when it is not found in the device repository. For example, the system can know that the using mobile browser in Table 4.3 is *VF-NetFront,* whose version is *3.3*.

Again we use Levenshtein Distance (Paleo, 2007; WURFL, 2007) to match the client device's browser to the browser repository. Although the system can detect or substitute the features of mobile device according to *user agent* from http request, the system only gets most similar or static capabilities of mobile device at most times.

In addition, we may get other headers besides *user agent*, such as markup language and format of images supported, size of screen, etc. We can get more accurate capabilities of mobile device dynamically based on other headers from http request.

Table 4.4 Levenshtein Distance for Detection

Input

input s and t; // two strings of User Agent

set lengths of s, t to n,m;

construct a Matrix[n+1,m+1];

Output

Matrix[n,m];

S1: initialize the first row, column to 0..n, 0..m;

S2: foreach character s[i] in s (i from 1 to n)

S3: foreach character t[j] in t (j from 1 to m)

S4: if(s[i] == t[j]) cost = 0;

S5: else cost =1;

S6 endif

S7: a= Matrix [i-1,j] + 1;

S8: b= Matrix [i,j-1] + 1;

S9: c= Matrix [i-1,j-1] + cost;

S10: set Matrix[i,j] = Min(a, b, c);

S11: endfor

S12: endfor

Step II: Get more accurate capabilities according to other headers from http request.

Different mobile service providers provide different header information for the same feature. For example, *HTTP_X_JPHONE_DISPLAY* is used for screen size by Softbank, the third largest mobile service provider in Japan, and *HTTP_X_UP_DEVCAP_SCREENPIXELS* by KDDI, the second largest mobile service provider in Japan.

Here, we define different rules to detect features based on different header information. Enhanced algorithm is proposed in Table 4.5.

In case that the feature of device does not be detected by two algorithms, the system modifies the device database and provides a default device alternative for learners (usable size width: 120 pixels; markup language support: xhtml basic 1.1; character encoding: utf-8; image format support: gif 89a; maximum total page weight:

20 kilobytes; colors: 256 colors; http: http/1.0). Later, the system or content manager updates the features of device automatically.

Table 4.5 Enhanced Algorithm for Detection

```
Input
   capability; // get based on user agent
   all headers
Output
   capability
S1 get header rules based on capability
S2 foreach header[i] in headers
S3    if (header[i] in rule)
S4          modify capability based on rule
S5    else
S6        submit to database for future improving
S7    endif
S8 endfor
```

4.3.3 Evaluation on Device Detection

Mobile phone, PDA, smart phone, iPod, and simulator (Some devices not included in the device repository) are tested. The database is created with same model with WURFL (2007). The proposed methods can detect the attribute values (the screen size, mobile browser, and image format) from PDA, smart phone, iPod, and simulator, which can detect more than WURL (2007) general model.

The proposed model has been applied into real system, called Rank10 (2010), which provides the information based on text, image, audio and document for users on ubiquitous devices. Everyday the wireless services from Rank10 (2010) are accessed more than 10,000 times. The test data are collected from Rank10 (2010). The detection results are displayed in Table 4.6 and Table 4.7 separately.

Table 4.6 Detection from WURFL Model

Type	Total Count	Screen size	Mobile Browser	Image format
Phone	68	58	65	52
PDA	3	3	3	3
Smart Phone	1	1	1	1
iPod	1	1	1	1
Simulator	2	2	2	2

Table 4.7 Detection from Proposed Model

Type	Total Count	Screen size	Mobile Browser	Image format
Phone	68	66	65	61
PDA	3	3	3	3
Smart Phone	1	1	1	1
iPod	1	1	1	1
Simulator	2	2	2	2

To advanced ubiquitous devices, such as PDA, iPod, the results are same by WURFL and proposed model from Table 4.6 and Table 4.7. The Fig. 4.3 shows that the detection results are different between WURFL and Proposed models. WURFL model in Fig.4.3 detects screen size (85.3%), mobile browser (95.6%), and image format (76.5%) of mobile phones. In this research, the all context data are used to detect the features of device based on proposed advanced method. Finally, the system can know screen size (97.1%), mobile browser (95.6%), and image format (89.7%) of mobile phones.

In fact, the popular ubiquitous devices used are mobile phones. The most important features of devices are image format and screen size when users access contents by mobile browsers. The proposed method may detect more models' features than those from WURFL method. So the proposed model is better applied for mobile application than WURFL model.

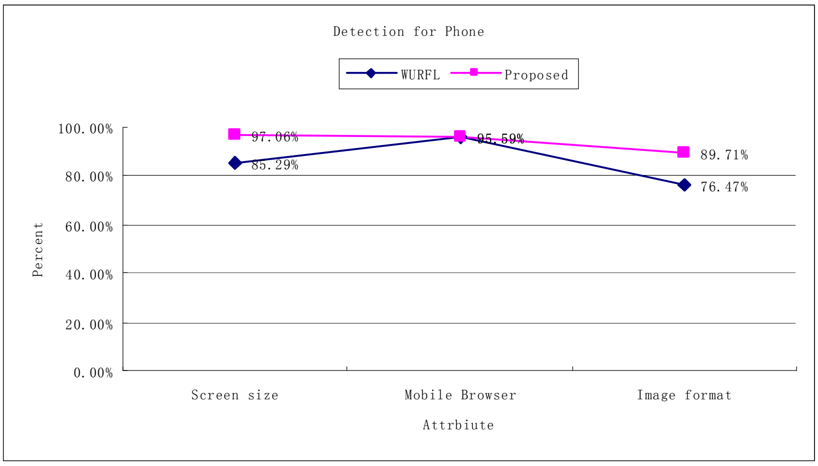


Fig.4.3 Comparison for Phone

4.4 Delivery Mechanism

Delivery model computes the presentation preference according to learning state: online or offline. If the learner is offline, the system sends adapted contents in sms, mms or mail. When the device supports mobile browser using by learner online, the presentation module inserts suitable markup language (HTML, WML, XHTML MP or cHTML) into transcoded & untranscoded contents from Adaptation Model. Table 4.8 gives the production (rules) for delivery mechanism.

Table 4.8 Productions (Rules) for Delivery

(R1 send-adapted-contents-to-device
(is, ?x adapted-contents)
(is, ?t format-of-adapted-contents)
(is-contained-in, ?t ?y)
(is-contained-in, ?m ?y)
(is-contained-in, ?n ?y)
(expression,, ?m≥?n)
==>
send ?x+?m to device)

For example, the adaptation presentation code is shown in Table 4.9. The learning object based on jpg image embedded into html for pc is shown in Table 4.10. The transcoding model creates adapted image for learners with html MP markup language shown in Table 4.11. Another adapted image for 2G device is shown in

Table 4.12.

Table 4.9 Adaptive Source Code

```
<Mobi:doctype/>
<Mobi:html>
  <Mobi:head>
  </Mobi:head>
  <Mobi:body>
    <Mobi:div id="image">
      <Mobi:img src="train.jpg"
alt="train"/>
    </Mobi:div>
  </Mobi:body>
</Mobi:html>
```

Table 4.10 HTML Source Code

```
<html >
  <head>
  </head>
  <body>
    <div id="image">
      <img     src="train.jpg"
alt="train" />
    </div>
  </body>
</html>
```

Table 4.11 HTML MP Source Code

```
<!DOCTYPE html PUBLIC
"-//WAPFORUM//DTD XHTML Mobile
1.0//EN"
"http://www.wapforum.org/DTD/xhtml-
mobile10.dtd">
<html >
  <head>
  </head>
  <body>
    <p>
      <img src="train.gif"
alt="train" />
    </p>
  </body>
</html>
```

Table 4.12 WML Source Code

```
<?xml version="1.0"?>
<!DOCTYPE       wml       PUBLIC
"-//WAPFORUM//DTD            WML
1.1//EN"
"http://www.wapforum.org/DTD
/wml_1.1.xml">
<wml>
  <card  title="image">
    <p>
      <img    src="train.wbmp"
alt="train" />
    </p>
  </card>
</wml>
```

Another, the communication fee is high when learner accesses learning content. So the system may try to send adaptive contents by sms according to learning state, e.g. the system may send discussion message to learner by mms.

On the contrary, the system sends image to learner by mms if the learning state is urgent, e.g. a latest updated contents or a notice to learners.

The Fig. 4.4 shows the adapted contents for courseware based on PowerPoint on different devices, which are from 3G phone, pda, and 2G phone.

When the learner accesses the ppt file on mobile device, the AubiLearn creates all indexes for each slide of ppt files. Learners may use the slide-index to review the learning contents based on mobile pages, which contains text and image data.

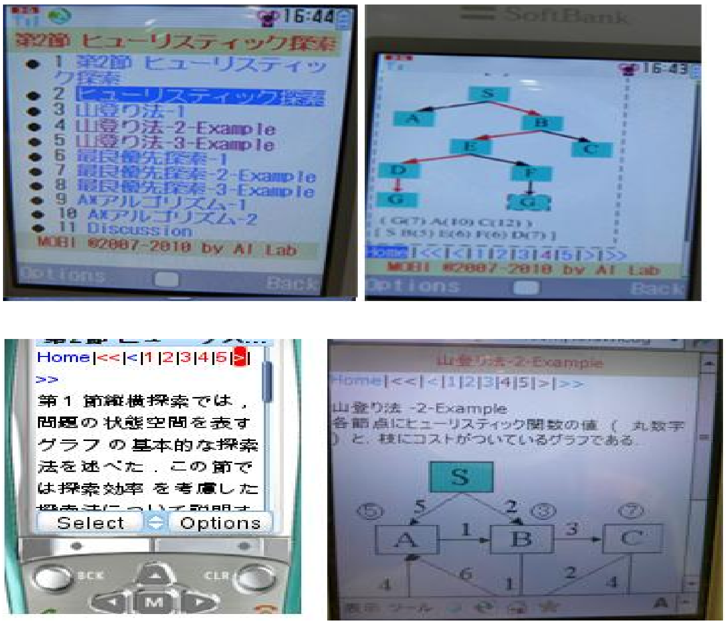


Fig.4.4 Snapshots of Adaptation Contents for PPT Files

4.5 Summary

This chapter mainly explains details about the detection for ubiquitous device and presentation service. First, definitions for adaptation methods are discussed in details. Then, the context reasoning method for device detection is proposed. The detection result is compared with other detection models, which shows that proposed method has better detection performance. Last, adaptive presentation mechanism is also explained in details.

Next chapter will introduce the details for adapted contents realization (content service and transcoding service). Also, AubiLearn prototype system is tested by rich media based on proposed methods, e.g. adaptive discussion and standard documents.

Chapter 5

Content Service & Transcoding Service

Objectives

This chapter explains:

- Adaptation Mechanism
- Transcoding Mechanism
- Evaluation on Adapted Contents
- Evaluation on Learners

Overview

This chapter explains the main technology contribution to content service and transcoding service to create adaptive content for ubiquitous learning environment. First, the adaptive content decision methods, including contextual module and situational module, are explained on focus. Based on the suggestions from adaptive decision methods, the transcoding methods realize the adapted contents for learners finally. Also, a cached mechanism is proposed to reduce the transcoding time. According to two different experiments, the results show that adaptation method can meet the transcoding threshold. Last, the evaluation is conducted on AubiLearn prototype system. The results show that the learners may get better learning experience through AubiLearn.

5.1 Introduction

In general, the ubiquitous learning system can provide a seamless learning process, by which learner may access learning objects at any time, any place with any device (Adriana, Ion and Marian, 2008; Haruo, Kiyoharu, Yasufumi and Shiho, 2003; Jones and Jo, 2004). A special characteristic of mobile device is that the learner can get instant contact with classmates or help from teacher (Motiwalla, 2007). Also, Motiwalla (2007) suggests that the learning system should provide a continuous two-way conversations and interaction among participants in order to get a successful education. The system should determine what version of contents should be adapted, e.g. pdf to html or gray image (Lum and Lau, 2002a), learning template for learners (Chang, Hung, Wang, Weng, Shih Timothy and Lee, 2008). Of course, the system also defines the semantic of contents for transcoding (Hsiao, Hung and Chen, 2008).

This research proposes a new method based on parallel production system (two working memories: context and situation), which dynamically transcodes the e-learning contents according to learning context and situation. Contextual method determines that the learning preference (preferred media type) and situation method provides adaptive contents according to learning context (device, network, and learning preference). Our transcoder analyzes the original learning objects (not written specifically for mobile phones and devices and thus not displayed properly or stored) and converts it to a mobile-ready format. At last, the learning system pushes recoded contents to remote learners, which contents are adaptive to learner’s preference, also to learner’s context.

5.2 Adaptation Mechanism

Content adaptation is not just about adapting to the device, but also the learner, the network, location, etc(Lau and Lum, 2003; Ogata and Yano, 2004; Vitor and Maria, 2009; Xu, Zhu, Zhang and Gu, 2008; Yang, 2006). In order to get adaptive contents for ubiquitous learning environment, the system should know: what you can you, what you have done, what you are doing according to learner’s request, learning social network, and past learning activities. Besides the features of device, the system also considers learning state (such as aims, interest, location…), educational state (requirements, purpose, results…), and learning environment (weather, place, neighbor, device...) generally. So One-Size-Fit-All is not a better way to provide contents for learners.

At first, this research recommends what contents media types are preferred. Then accessed contents recoded/reorganized are pushed to remote learners. In order to resolve the confliction among content service, this research introduces the parallel production system mechanism into u-Learning (shown in Fig.5.1).

Each memory contains different contextual data coming from learner or server.

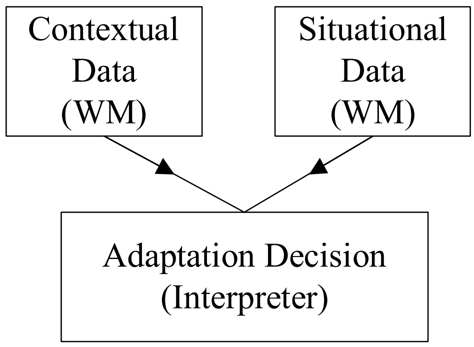


Fig. 5.1 Working Memory (WM) & Interpreter in u-Learning

Two working memories (WMs), contextual data and situational data, are proposed to monitor the context awareness from learner and server. The interpreter, adaptation decision, determines the action according to new data from two working memories. The productions can then infer many new states from the existing state according to data of two working memories.

5.2.1 Contextual Mechanism

In this research, contextual module recommends media presentation preference according to contextual data: learning time, learning place, device type and learning objects, which is shown in Fig.5.2. The reward-penalize method is used to resolve the confliction for content service in Fig.3.4.

Input: Learning media component, learning time, learning location, and device type
Output: preferred media type

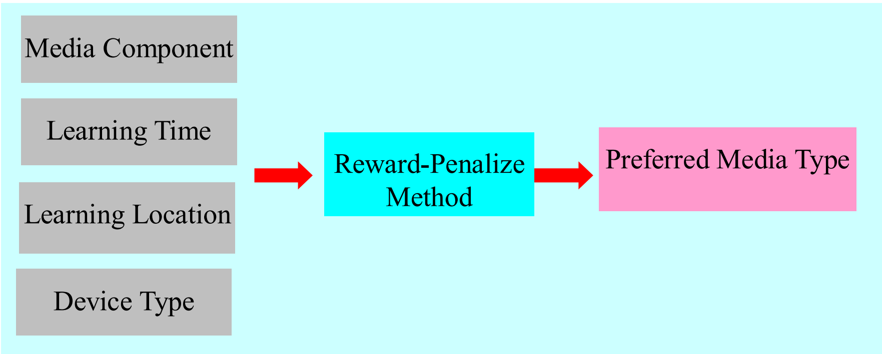


Fig. 5.2 Contextual Module

If the learning response is favorable (success), then we reward the selected media presentation type, while if the learning response is unfavorable (failure), then we penalize the selected media presentation type. We reward (penalize) the selected contents preferred media type according to how much favorable (or unfavorable) learning response was. If the environment response is very favorable, the selected action is rewarded very much. On the other hand, if the learning response is marginally favorable, the selected action is penalized very little. Similarly, if the learning response is very unfavorable, the selected action is heavily penalized, and if the learning response is marginally unfavorable, the selected action is marginally penalized. In this research, the learning context in contextual module is defined by u_i=[learning time; learning location; device type; learning object] and the learning action in contextual module is defined by $r_i(t)$=[learning object presentation type].

At each time t, the selected preference is $r(u_i) = r_i, r_i \in \{r_1, r_2, ..., r_n\}$ with probability $p_i(t) = p[r(u_i) = r_i]$. The selected preference $r(u_i)$ is looked as the context input to the learning environment. If this results in a favorable environment response, then the probability $p_i(t)$ is increased by $\Delta p_i(t)$ and the $p_j(t)$, $i \neq j$ are decreased by $\Delta p_i(t)$. Otherwise, if unfavorable environment response appears, then $p_i(t)$ is decreased by $\Delta p_i'(t)$ and the $p_j(t)$, $i \neq j$ are increased by $\Delta p_i'(t)$. This behavior is shown in formula below.

Preferred Media Type$_{LO}$ ***$(i \rightarrow j)$ received positive response:***

$$\begin{cases} P_{ij}(t)=P_{ij}(t)+\Delta P_i(t)(1-P_{ij}(t)) \\ P_{ik}(t)=P_{ik}(t)\cdot(1-\Delta P_i(t)), k\neq j \end{cases} \qquad Formula.5.1$$

Preferred Media Type$_{LO}$ ***$(i \rightarrow j)$ received negative response:***

$$\begin{cases} P_{ij}(t)=P_{ij}(t)-\Delta P_i'(t)(1-P_{ij}(t)) \\ P_{ik}(t)=P_{ik}(t)\cdot(1+\Delta P_i'(t)), k\neq j \end{cases} \qquad Formula.5.2$$

We call the process reward-penalize method. In general, it uses one response to realize (Economides, 1996; Kyriakakos, Hadjiefthymiades, Frangiadakis, Merakos, 2003; Ortiz, Simpson, Pignatiello, Heredia-Langner, 2004). In this research, we introduce multiple responses algorithm for contextual module. The method is to use different adaptation rate for different learning response. When the learner's response is very good, we heavily reward the selected preferred media type by increasing its probability rapidly. When the response is marginally good, we correspondingly reward the selected preferred media type by increasing its probability slowly. On the contrary, whenever the learning response is very bad, then we heavily penalize the selected preferred media type by decreasing the probability very fast. When the learning response is not so bad, we penalize the selected preferred media type less strictly by decreasing its probability slowing. According to six status values of SCORM (2004) data model definition (Passed, Failed, Completed, Uncompleted, Not Attempted, Browsed), t response is defined in Table 5.1.

Table 5.1 Response of Learning Objects

R2	*Learning, then go on next learning object*	*reward*
R1	*Learning and stop*	*reward*
R0	*Learning object not used*	*reward*
P0	*Learning, but change other media type*	*penalize*
P1	*Instantly change other media type*	*penalize*

In this research, a sequence for the reward-penalize response is a Fibonacci sequence (normalized to the [0, 1]). The R0 is the threshold for a response to be considered as reward or penalty. For the five level Fibonacci sequence, the value should be 0, 1/3, 1/3, 2/3, 1.

For different learning level, the selected preferred media type is different. So we can not look the recommended and self-selected contents as same weight during learning. This research divides all contents studied under learning context u_i into two categories: recommended contents and self-selected contents. The research assigns α to recommend preferred media type, in contrast, self-selected contents $1-\alpha$. Different α means different functionality.

$$\begin{cases} p_R = \alpha, & R: I \rightarrow \text{Type T (Recommendation)} \\ p_S = 1-\alpha, & S: I \rightarrow \text{Type T (Self - selection)} \end{cases} \quad 0 \le \alpha \le 1$$

For example, for primary learning, the system should recommend suitable preferred media type for learners usually. But for adult learning, the learners can determine the learning objects by themselves under their knowledge.

$$\alpha = \begin{cases} \alpha \ge 0.5, & \text{recommended contents is more important, e.g. for primary learning} \\ \alpha = 0.5, & \text{same priority} \\ \alpha \le 0.5, & \text{Self - selected contents is more important, e.g. for colledge learning} \end{cases}$$

The learning preferred media type is categorized into four groups (A, B, C, and D) according to learning context u_i, which are:

A: *Learning objects under context* u_i

B: *Learning objects studied with type (I) within set A*

C: *Learning objects studied T within set B*

D: *Learning objects studied by T and I within set C*

The probability $p_T(t)$ of the preferred rank value of MIME type (T) under context u_i is computed by Formula 5.3.

$$p_T(t) = \frac{\sum_{j \in D} p_{T,j}(t) / \sum_{j \in C} p_{T,j}(t)}{\sum_{j \in B} p_{T,j}(t) / \sum_{j \in A} p_{T,j}(t)} \text{------} \Big|_{Formula\ 5.3}$$

The rank of preferred media type is used in this research to improve the QoS

(Quality of Service) of adaptive contents. At last, the above concepts lead us to formally define the MR-RP(Multiple-Response reward-penalize) algorithm in Table 5.2.

Table 5.2 MR-RP(Multiple-Response Rreward-Ppenalize) algorithm

Input

Context u_i

Output

Preferred Media Type;

Algorithm

Initialize the $p_i(t)$

forEach k in Response

If (k=favorable) then

$p_i = p_i + R \cdot (1 - p_i)$

$p_j = p_j \cdot (1 - R), j \neq i$

endFor

forEach k in Response

If (k=unfavorable) then

$p_i = p_i - P \cdot (1 - p_i)$

$p_j = p_j \cdot (1 + P), j \neq i$

endFor

$p_i(t) = p_i(t) + p_i / \sum n$

$p_j(t) = p_j(t) + p_j / \sum n, j \neq i$

Preferred Media Type = $\begin{cases} Type(Mediaconponent) & p_i(t)=p_j(t), i \neq j; \\ Max(p(t)), & \text{others;} \end{cases}$

5.2.2 Situational Mechanism

Then, after situational module (Fig.5.3) negotiates the learning objects according to network features, and device capabilities, it creates the transcoding suggestion for adaptation decision module. The learning state in situational module is defined in

$U_i(t)$={<feature finite sate machine>|network feature, device capabilities, feature of learning media component, preferred media type}.

Input: media presentation preference, learning media component, network features, device capabilities
Output: suggestion of target learning media component

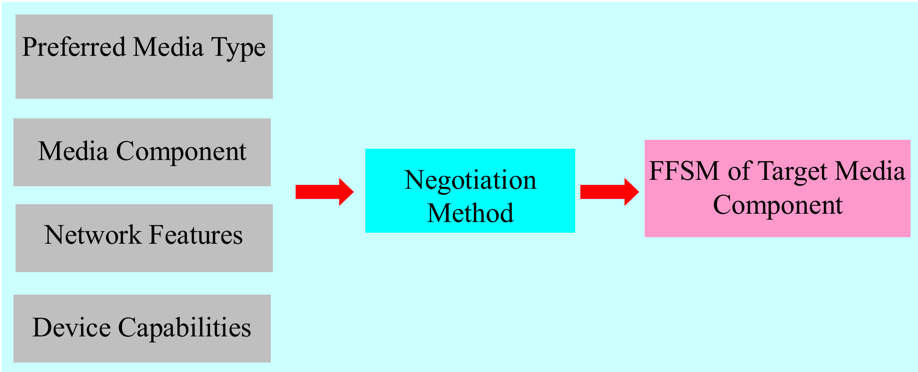


Fig. 5.3 Situational Module

Situational Module will create a feature finite state machine based on media presentation preference, feature of learning media component, feature of networks, and feature of device. A FFSM represents the constrained features of one component(I) from initial state feature to final state feature set.

Feature Finite State Machine is a kind of finite state machine, which is a model of computation consisting of a set of states, a start state, an input alphabet, and a transition function that maps input symbols and current states to a next state. Computation begins in the start state with an input string. It changes to new states depending on the transition function.

Feature Finite State Machine (FFSM) is a quintuple (Σ, S, s_1, δ, F), where:

.Σ is the input alphabet (a finite, non-empty set of symbols).

.S is a finite, non-empty set of states, represents the feature of contents, context.

.s_1 is an initial state, represents the original feature of contents or learning object.

.δ is the state-transition function; condition of state-transition is the contextual data: device, place, learner's preference, and so on.

.F is the set of final states, a (possibly empty) subset of S.

s_1 is the initial state, which represents the initial feature value of contents. So it has higher value than other state. The value of state s in FFSM is changing smaller from one state to another state. The closer the state is to the initial state, the larger the value of the state is. On the contrary, the closer to final state, the smaller the value of state is.

In this research, the weight of Item-Context is used to decide feature finite state machine.

Weight of Item-Context (W) is a set for a learning media component contrasted to context,

W = {w_i| w_i=<f_i,v_i>, $f_i \in SO_I$, $v_i \in SC_{If}$=[0,1]: weight for context-aware, i∈[0,n]};

-Where, n is the total count of media component features.

v_i means feature i has priority degree to transform, the larger value, the higher priority, which is computed.

$$w_{component}(feature.i) = \begin{cases} 1 - Min\left\{\dfrac{v_{context}}{v_{conponent}}\right\}, & feature{\cdot}i \text{ is multidimensional value;} \\ 1 - \dfrac{v_{context}}{v_{conponent}}, & feature{\cdot}i \text{ is single value;} \end{cases} \quad - \Big| Formula.5.4$$

For example, a ppt learning media component (I) with 200kb is accessed by mobile phone. Of course, the mobile phone does not support standard file: powerPoint. Also, the mobile phone only supports max size of contents: 30Kb. Fig.5.4 is partial FFSM of learning media component (I) for adaptation. The weight of item-context W(I)={<format, 1>, <size, 0.85>}, whose values are computed by

$$w_{a.ppt}(format) = 1 - \frac{0}{1} = 1$$
$$w_{a.ppt}(size) = 1 - \frac{30k}{200k} = 0.85$$

S_1 is initial state. From initial state S_1, the contents can be adapted according to different format: xml, jpg, gif,…

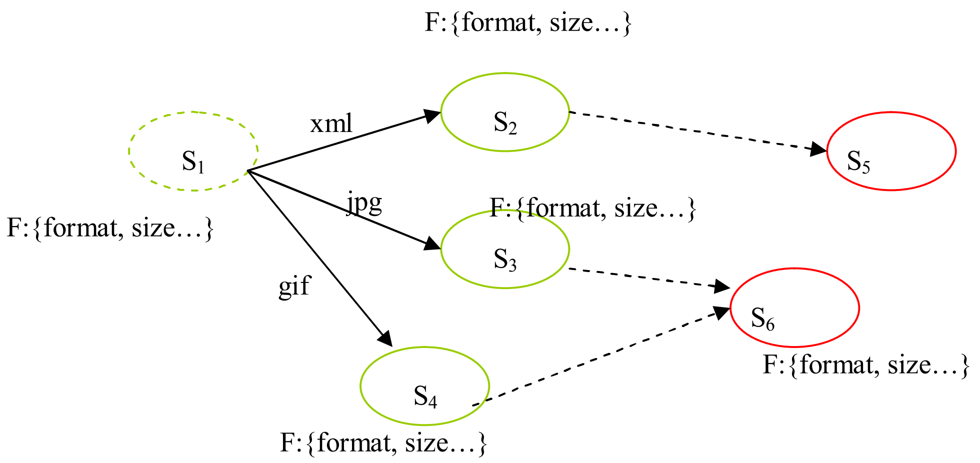


Fig. 5.4 FFSM Model

High Feature Sub-Set Operator ⊗ (C=A⊗B):

$$C = A \otimes B = \left\{ c \left| \begin{array}{l} c =< f, v_a >, if \ f \in A \cap B, v_a(f) \geq v_b(f) \\ \text{or} \ c =< f, v_a >, if \ f \in A, f \notin B \end{array} \right. \right\}$$

Property I. Let s, $s_f \in S$, s_f represents constrained feature of ubiquitous device. Then there must exist a path p from initial or cached state (s) to final state (s_f).

As follows:

Suppose $S_{FFSM_{SO}}$ is state set of FFSM of learning object o, $C = s \otimes D, s \in S_{FFSM_{SO}}$

1. if $C = \phi$, it means that feature of s is smaller or equals with D, contents with s_f can be played on current device;

2. if $C \neq \phi$, it creates a state-transition from s to a new state n , $s \xrightarrow{\sigma:f} n$, $f \in s, n, v_{SO_{sf}} \geq v_{SO_{Df}} \approx v_{SO_{nf}}$

3. $C = n \otimes D$

4. repeat 2,3 until $C = \phi$.

At last, we can get $C = \phi$. So we must get a path from any cached state to a target device.■

In order to complete the transcoding request from application, the transcoding model chooses one or more suitable transcoders (T) to recode original contents (OC) into adapted contents (AC). Suppose that the transcoding process needs *n* transcoders (T_i). The transcoders (T) may be image, audio, and video transcoders. The transcoding process is like natural code and state transition in Table 5.3 and Fig.5.5 separately. The total transcoding time should be

$$Time = \sum time_{T_i}$$

OC: initial content for transcoding
AC: adapted content after transcoding
T_i :mid-adapted contents during transcoding

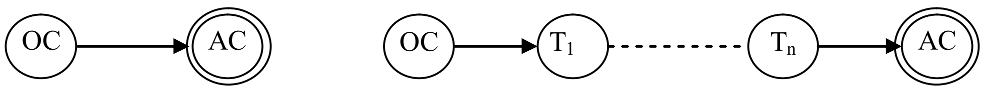


Fig. 5.5 Transcoding Selection Chain on FFSM Model

Table 5.3 Transcoding Process(Lemlouma, 2004)

Step 1 original content = OC;
Step 2 from 1 to n do
Step 3 AC = T_i(OC);
Step 4 return AC;

Property II. There must exist a Minimum Cost Path (MCP) from cached state to target state (s_f).

As follows:

From Property I, we can find at least a state to target state s_f.

Suppose $S = \{s \mid s \text{ is reachable to } s_f\}$, C_s is the cost from state s to state s_f

$$C_s = \sum_{i,j} \cos t_{i,j}\ , state\ i \text{ is reachable to state j}$$

So $MCP = Min\{C_s\}$ ■

The Table 5.4 describes the details of creation of FFSM for component(I) according to preferred media type, learning media component, network feature, and device capabilities.

Table 5.4 Negotiation Algorithm Based on FFSM

Input

I, C, FFSM;// component feature and context

Output

FFSM;// feature finite state machine of component

Algorithm

create $R = \{<t_i, v_i> \mid t_i \in \{mime\ type\}, v_i \subseteq \{<f_{ij}, v_{ij}> \mid f_{ij}: \text{one feature of } t_i, v_{ij}: \text{value of } f_{ij}\}\}$

if(FFSM is null) create initial state s_0 *of FFSM;* $s_0(fv,fv',r) = (I, I, R)$;

push(s, s_0*); // s: state stack*

while(stack_not_empty(s))

$s_{curRoot}$ = pop*(s);*

$M = MAX\_WEIGHT(s_{curRoot}(r))$; *// find max weight value*

$T = \{ f_j \mid f_j \in s_{curRoot}(fv) \text{ and } w_{fj} \in M\}$;

forEach f_j *in T*

create a new edge: $s_{curRoot} \xrightarrow{f_j} s_{nextState}$, *which satisfies:*

$s_{nextState}(fv) = s_{curRoot}(fv) - s_{curRoot}(f_j) + D(f_j)$;

$s_{nextState}(fv') = s_{curRoot}(fv') - \{<f_j, v_j>\}$;

if($s_{curRoot}.t = s_{nextState}.t$*)*

$s_{nextState}(r) = s_{curRoot}(r) - M$;

else

$s_{nextState}(r) = R.t$;

endIf

push(s, $s_{nextState}$);
endFor
endWhile

5.2.3 Adaptation Decision Mechanism

Generally speaking, the adaptation decision process can be seen as learning object allocation in a generalized learning objects distortion framework. Given a set of available learning context data, it selects the set of contextual parameters that lead to a given variation of the content, trying to satisfy ubiquitous learning environment. It is responsible for deciding how the system should react.

In this research, the learning preferred media type, learning time & location, device capabilities & types, download/upload speed, and network type are used as the contextual & situational data. So, the following patterns in Table 5.5 are used to define the production & working memory.

Table 5.5 Patterns of Contextual & Situational Data

Patterns	*Example on Factors*
1. (is, ?x ?y)	*The learning location is on the road*
2. (is-contained-in, ?c ?o)	*The type PDA is contained in device type*
3. (equal, ?s ?t)	*The size of learning media component equals 100Kb*
4. (expression, ?u ?op ?v)	*The dimension of the device is smaller than (≤)those of learning media component*
5. (support-the-feature, ?p ?q)	*The device supports the gif image*

According to the patterns above, we give the production (rules) for contextual module, situational module, and adaptation decision. These rules shown in Table 5.6, 5.7, 5.8 are produced according to the patterns in Table 5.5.

Table 5.6 Productions (Rules) for Contextual Module

```
(R1 check-whether- preferred-media-type-existing
     (equal, ?x nil)
     (is, ?x preferred-media-type)
     (is, ?y learning-media-component)
     (is, ?t learning-time )
     (is-contained-in, ?m ?k )
     (is, ?k device-type )
     (is-contained-in, ?n ?l )
     (is, ?l learning-location )
 ==>
    Compute- preferred-media-type
   delete ?y, ?t, ?m, ?n)

(R2 get-next- preferred-media-type
     (is, ?x preferred-media-type)
 ==>
     delete ?x
    get-top- preferred-media-type)

(R3 get-top- preferred-media-type
     (is, ?x preferred-media-type)
     (is, ?y preferred-media-type)
     (expression, ?x≥?y)
 ==>
   return ?y)
```

Table 5.7 Productions (Rules) for Situational Module

```
(R1
check-whether-ffsm-existing-for-learning-media-component
    (equal, ?x nil)
    (is, ?x ffsm)
    (is, ?i learning-media-component)
    (is, ?n network-features )
    (is, ?d device-capabilities)
==>
    create ffsm
    delete ?i)

(R2 adjust-ffsm-for-learning-media-component
    (is, ?x ffsm)
    (is, ?y preferred-media-type)
    (is, ?n network-features )
    (is, ?d device-capabilities)
    (support-the-feature, ?d ?y)
==>
    adjust ffsm
    delete ?y)
```

Table 5.8 Productions (Rules) for Adaptation Decision Module

```
(R1 check-whether-learning-object-existing
    (is, ?x learning-object)
==>
    create-learning-media-component-set
    delete x)

(R2 check-whether-learning-media-component-existing
    (is, ?x learning-media-component )
    (is-contained-in, ?x learning-media-component-set)
==>
    send ?x to two working memories
    delete ?x)

(R3 check-whether-final-state-existing
    (is, ?f ffsm)
    (is-contained-in, ?x ?f)
    (is, ?y learning- preferred-media-type)
    (support-the-feature, ?y ?fy)
    (support-the-feature, ?x ?fx)
    (equal, ?fx ?vx)
    (equal, ?fy ?vy)
    (equal, ?vy ?vx)
==>
    insert ?x into final-state-set
    delete ?x)

(R4 adjust- preferred-media-type-in-ffsm
    (equal, ?x nil)
    (is, ?x final-state-set)
==>
```

change preferred-media-type in situational memory)

(R5 delete- preferred-media-type-from-contextual-memory

(is, ?x ffsm)

(is, ?y ffsm)

(expression, ?x =?y)

==>

delete preferred-media-type in contextual memory)

(R6 create-transcoding-job-from-final-state-set

(is-contained-in, ?x final-state-set)

(is, ?s learning-media-component-size)

(is-contained-in, ?sx ?x)

(is, ?sx learning-media-component-size-in-state)

(expression, ?sx < ?s)

(is, ?d learning-media-component-dimension)

(is-contained-in, ?dx ?x)

(is, ?dx learning-media-component-dimension-in-state)

(expression, ?dx < ?d)

(is, ?c learning-media-component-color-depth)

(is-contained-in, ?cx ?x)

(is, ?cx learning-media-component- color-depth-in-state)

(expression, ?cx < ?c)

(expression, $?t_r < ?t_t$*)*

(is, $?t_r$ *response-time)*

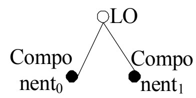
(is, $?t_t$ $t_{threshold}$*)*

==>

create transcoding job

delete ffsm, device-capabilities, network-feature)

In order to create adaptive contents appropriate for the learning context, learning objects accessed should be reorganized on the basis of contextual module and situational module. First, learning object accessed is parsed into different learning media components. E.g., the system creates a LO tree nodes for learning object in Table 4.1. Component_0=*{<format, text>,<size, 405bytes>},* Component_1=*{<format, image>,<src, http://upload.wikimedia.org/wikipedia/en/3/39/Java_logo.svg>, <size, 70kb>, <alt, java>}*. Then, the preferred media type of each learning media component is created by contextual module, e.g. $P_{\text{Component}0}$ = *{<format, audio>, <volume, 4>, <channel, 1>}*.



Another, after the learner submits a request for some learning objects, the system should deliver the adaptive contents as soon as it can. The whole learning objects delivery process will suffer a number of delays, such as transmission delay on the fly and the transcoding time of the adaptation process (Lum and Lau, 2002b). We may use the transition cost of states to control the delay time so as that the learner can tolerate it.

Transition Cost of States $c_{i,j}$ is the cost from state i to state j, which are computed by different transformation in Fig. 5.6.

$$c_{i,j} = n \times t$$

where t is transcoding time for one unit of contents from state i to state j; $n = \frac{Size}{Unit}$ is the total units of transcoding source contents.

> In general, the transcoding process will be from state i to state j; there may be zero, one or more states between i and j

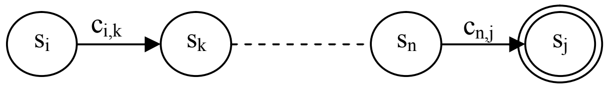


Fig. 5.6 Transcoding Time Cost

Totally, the transcoding time $T = \sum c_{i,j}$. Based on the definition of $c_{i,j}$, we can compute the learner-perceived response time (C) will be

$$C = 2 \times RTT + \frac{S}{B} + T + m = 2 \times RTT + \frac{S}{B} + \sum c_{i,j} + m \le t_{threshold} \quad --Formula 5.5$$

where RTT is the network roundtrip time latency between the client and the e-learning system; is $\frac{S}{B}$ the transmission time of contents on the fly; m is means waste time for contents (e.g. creation xml, negotiation, etc.); $t_{threshold}$ is the maximum transmission time that the learner can put up with.

Based on the $FFSM_i$ of learning media component i, the adaptation decision module creates a lowest transcoding cost path from initial state to final state set. According to the transcoding cost, adaptation decision module creates a transcoding job for learning media $component_i$.

Finally, adaptation decision module creates transcoding jobs for learning media components. To further illustrate the idea, we can explicitly define the following as part of the decision logic(Lum and Lau, 2003) will return True if and only if the final state in $FFSM_i$ is

1. learning object size ≤device memory buffer; the objects conclude all learning resource, include text, image, or video. W3C-MWBP (2008) recommends that the content size is smaller than 30KB because today memory of most mobile devices is up to 30KB. In general, size of per page (S) = markup size + text size + image size < device memory buffer size (M);
2. content dimension ≤ acceptable device screen dimension; e.g. one image with 800X640 for device with 320X240.
3. color depth of the content ≤ acceptable color depth of the device;
4. $C = 2 \times RTT + \frac{S}{B} + T + m = 2 \times RTT + \frac{S}{B} + \sum c_{i,j} + m \le t_{threshold}$

This research has defined many rule bases for different learning object, such as the following xml code for PowerPoint transcoding. Different attribute of learning media component can be transcoded according to transcoding rule base.

For example, the following xml code is partially designed for PowerPoint file, whose mime type is application. The code means that PowerPoint file can be transcoded into image/gif (gif format), text/html (html format), and application/xml (xml format). According to the rules, the system may create adaptive contents (gif, html, or xml) for PowerPoint contents. At last, the system may use parallel production system to recommend suitable contents for learners. A FFSM created for xml code is shown in Fig. 5.7.

```
<rule name ="appliation">
    <r source="vnd.ms-powerpoint" target="image/gif" format="gif"/>
    <r source="vnd.ms-powerpoint" target="text/html" format="html"/>
    <r source="vnd.ms-powerpoint"  target="application/xml"
format="xml"/>
    <r source="xml"  target="text/html" format="html"/>
    <r source="xml"  target="text/vnd.wap.wml" format="wml"/>
    <r source="xml"  target="audio/x-wav" format="wav"/>
  </rule>
<rule name="text">
    <r source="html" target="audio/x-wav" format="wav"/>
    <r source="vnd.wap.wml" target="audio/x-wav" format="wav"/>
    <r source="vnd.wap.wml" target="text/html" format="html"/>
  </rule>
  <rule name="audio">
    <r source="x-wav" target="audio/amr" format="amr"/>
    <r source="x-wav" target="audio/amr-wb" format="amr"/>
  </rule>
  <rule name="image">
    <r source="image/gif" target="image/jpeg" format="jpg"/>
    <r source="image/gif" target="image/png" format="png"/>
  </rule>
```

The system will create a feature finite state machine for accessed learning objects: powerpoint learning objects. According to transcoding rule, a feature state machine is created at last. The system chooses one state for adaptation learning objects finally.

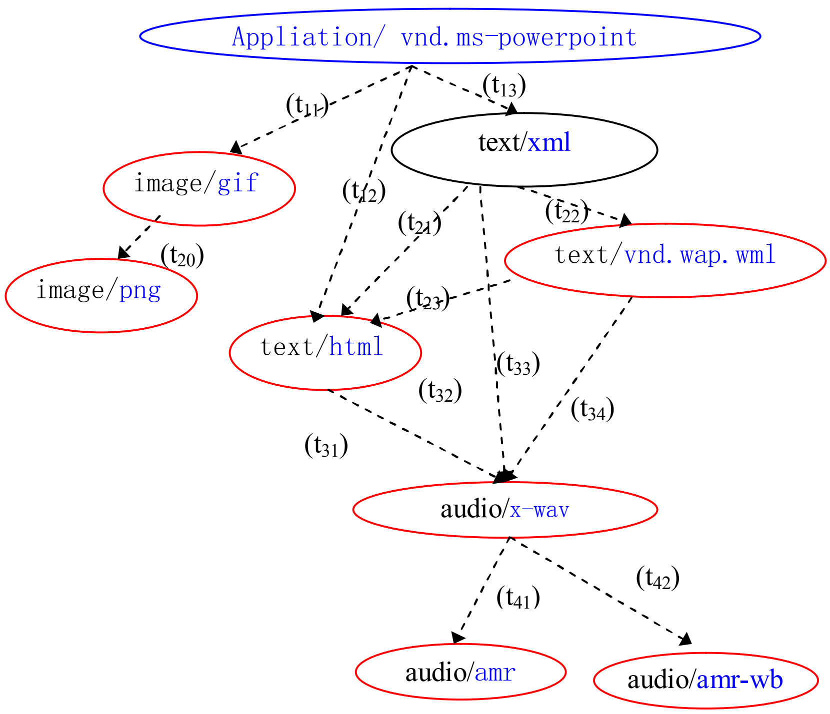


Fig. 5.7 Transition Rules for Learning Object Based on PowerPoint

Fig. 5.8 shows overview of our adaptation mechanism for creating adaptive learning media component. Contextual module and situational module are modeled and managed by the system. According to the component's preferred media types and situational data, the constrained feature based on ffsm is created for each learning media component. The constrained feature satisfies the learning environment.

State(●) in ffsm: *represents the feature of learning media component*

Feature in transition of ffsm: represents a attribute of Learning media component, e.g. s_0*---format(gif)--->*s_1

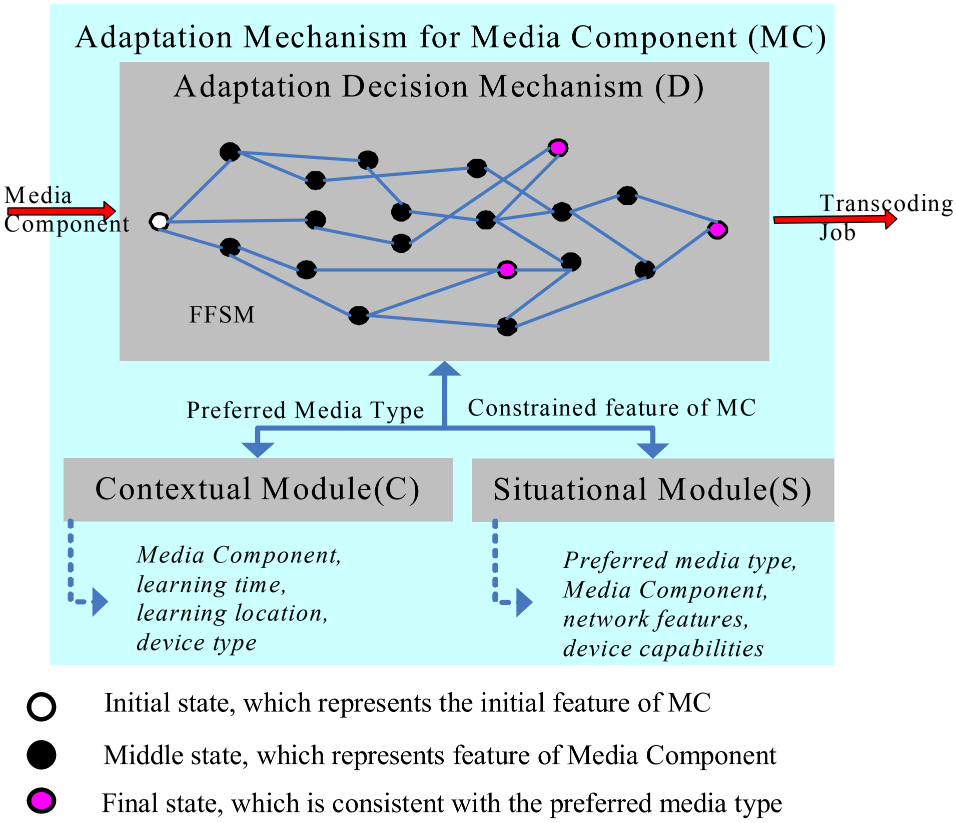


Fig. 5.8 Overview of Mechanism for Adaptation Learning Media Component

Simple decision logic to judge whether the learning media components can be supported may use rule base as follows

IF (x: type1→type2^x exists in type1 ^ feature(x)=Max[feature(y), y∈I(type1]))
THEN
return True
ELSE
return False

In general, the system only transcodes parts of original contents into adaptive contents. High Feature Sub-set determines what feature the system should transform at last based on original or cached contents. The adaptation decision algorithm is described in Table 5.9.

Table 5.9 Adaptation Decision Algorithm

Input

Learning object, learning context

Output

Transcoded Learning Object

Algorithm

job = null;

forEach $component_i$ *(learning media component contained in the learning object to be delivered)*

get preferred media type $< p_i >$ *from Contextual Module for* $component_i$

get suggested version $FFSM_i$ *from Situational Module for* $component_i$

find a lowest time cost set P from initial state s_1 *to final state* s_f *in* $FFSM_i$

if(!empty(P))

traverse the path p in P and get the constrained features

create a transcoding job_i *for* $component_i$

endIf

$job=job+job_i$

endFor

send the transcoding job to transcoding model

determine the transcoded learning media components to be delivered according to transcoding response from transcoding model

5.2.4 Results on Adaptation Mechanism on Real Web Application

In order to evaluate the adaptation mechanism, the adaptation mechanism has been installed on a real web system (Rank10, 2010), which provides general searching service for users (more 10,000 pages/day accessed by mobile users from the world). The users have been traced between April 19 and April 27, 2010. The reports for all users from different device visiting and pageviews are shown in Fig. 5.9.

There are many different devices detected by our proposed system. The screen size of device is from 1x1 to 640x320. The size with 240x320, 90x40, and 240x427 are most popular devices from users.

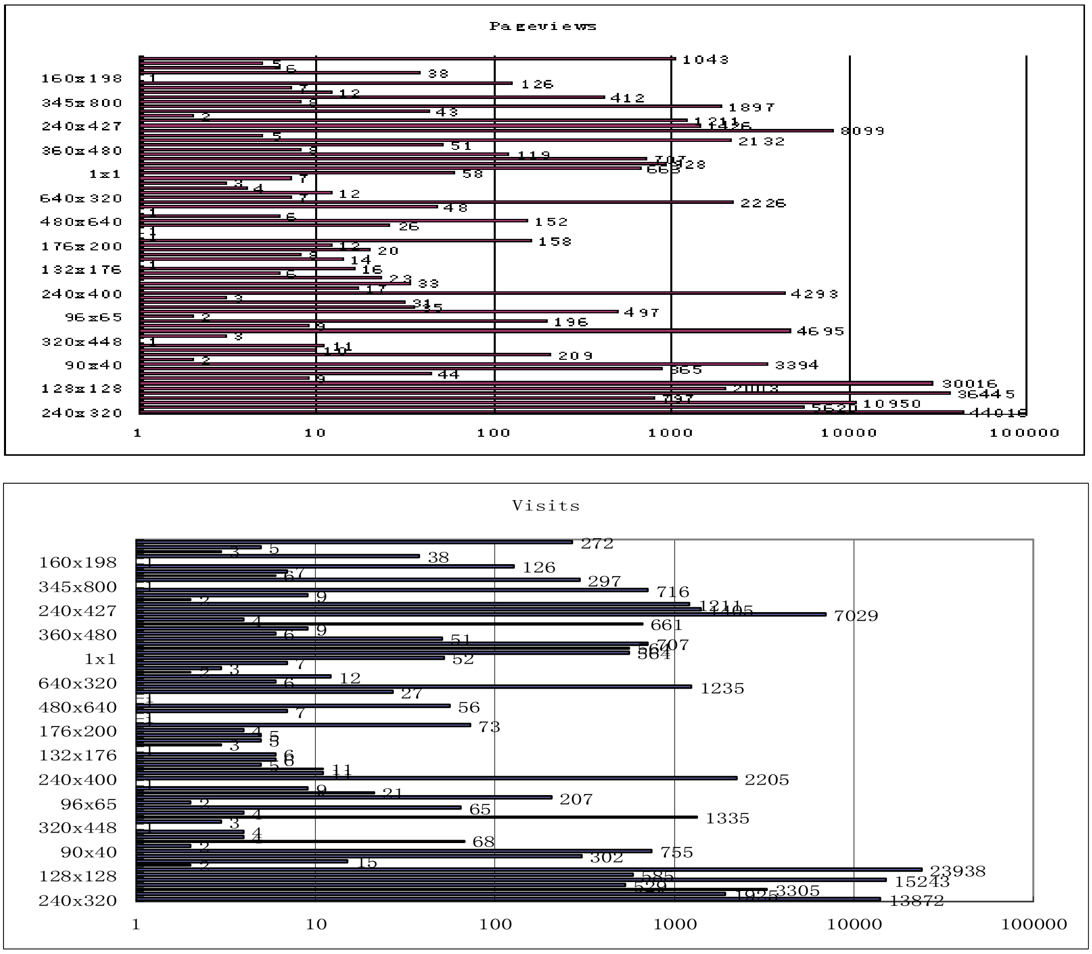


Fig. 5.9 Accessing Reports for All Devices

The results in the Fig. 5.9 show that there are many different devices existing today. Also, it has certified that the system should have to update the device bank dynamically everyday according to accessing from users. The system should consider more context data to create adaptive contents for users during ubiquitous environment. The Table 5.10 gives the all accessing reports from users. Here the average time including the downloading & watching/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. The system provided types of contents below: text, image, and audio according to user's experience. The Table.5.11 and 5.12 are two groups for accessing reports separately..

Table 5.10 Accessing Reports for All Users

Date	Unique Visitors	Pageviews	PVs/Visit	Avg. Time/Visit	Avg. Time/Page
20100419	4413	16105	3.65	73.3	20.1
20100420	5257	18458	3.51	79.8	22.7
20100421	5401	19428	3.6	90.3	25.1
20100422	5601	21610	3.86	88.3	22.9
20100423	4932	18490	3.75	81.6	21.7
20100424	5303	19281	3.64	82.2	22.6
20100425	4685	17660	3.77	73.9	19.6
20100426	4526	17295	3.82	72.4	18.9
20100427	4888	17641	3.61	77.9	21.6

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 that the contents were text message. For non-controlled group (II), the system just sends originally accessing contents for users.

From Fig. 5.10, we know that the visitors from group (I) access more pages than those from group (II), whose growth rate $((PV_I\text{-}PV_{II})/PV_{II})$ 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%).

Of course, the total time (=PageView x Agv.Time/visit) visiting from group (I) is more than that from group (II). Another, the users from group (I) may stay longer on each page than those from group (II), whose growth rate

((Avg.Time/$Page_I$-Avg.Time/$Page_{II}$)/ Avg.Time/$Page_{II}$) are within [10% (April, 22), 58 % (April, 19)], which is shown in Fig. 5.11.

Table 5.11 Accessing Reports from Controlled Group (I)

Date	Unique Visitors	PageViews	PVs/Visit	Avg. Time/Visit	Avg. Time/Page
20100419	2423	9570	3.95	93.3	23.6
20100420	2571	10827	4.21	102.8	24.4
20100421	2258	8800	3.9	114.3	29.3
20100422	2023	9424	4.66	112.3	24.1
20100423	2618	11647	4.45	101.5	22.8
20100424	2102	8904	4.24	105.2	24.8
20100425	2572	10209	3.97	89.9	22.6
20100426	1958	8265	4.22	96.4	22.8
20100427	2720	11859	4.36	106.0	24.3

Table 5.12 Accessing Reports from Non-Controlled Group (II)

Date	Unique Visitors	PageViews	PVs/Visit	Avg. Time/Visit	Avg. Time/Page
20100419	1990	6535	3.28	49.0	14.9
20100420	2686	7631	2.84	57.8	20.3
20100421	3143	10628	3.38	73.1	21.6
20100422	3578	12186	3.41	74.7	21.9
20100423	2314	6843	2.96	59.0	19.9
20100424	3201	10377	3.24	67.1	20.7
20100425	2113	7451	3.53	54.4	15.4
20100426	2568	9030	3.52	54.1	15.3
20100427	2168	5782	2.67	42.8	16.1

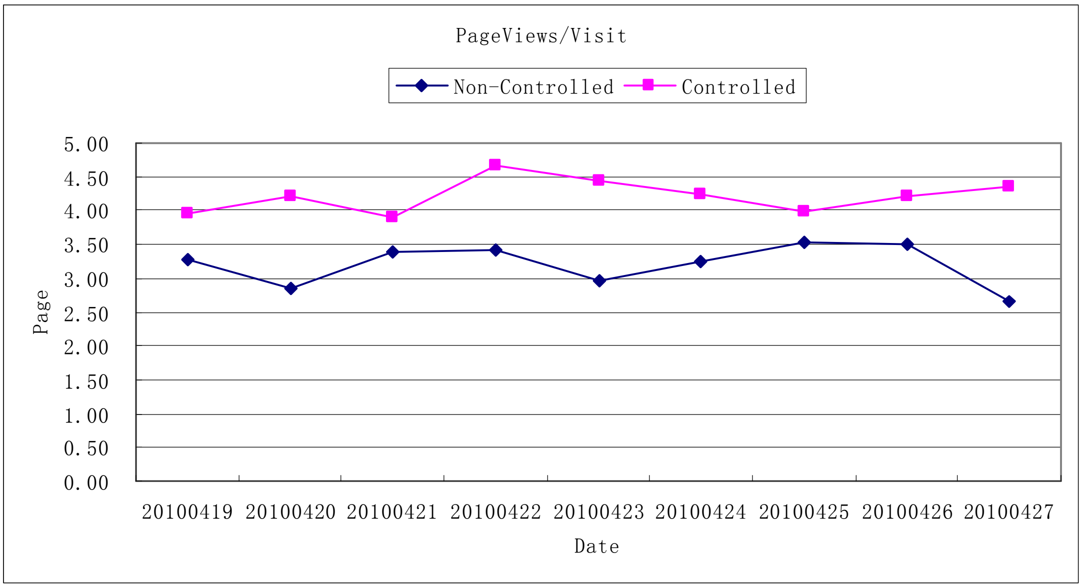


Fig. 5.10 Comparison of PageViews between between group (I) and group (II)

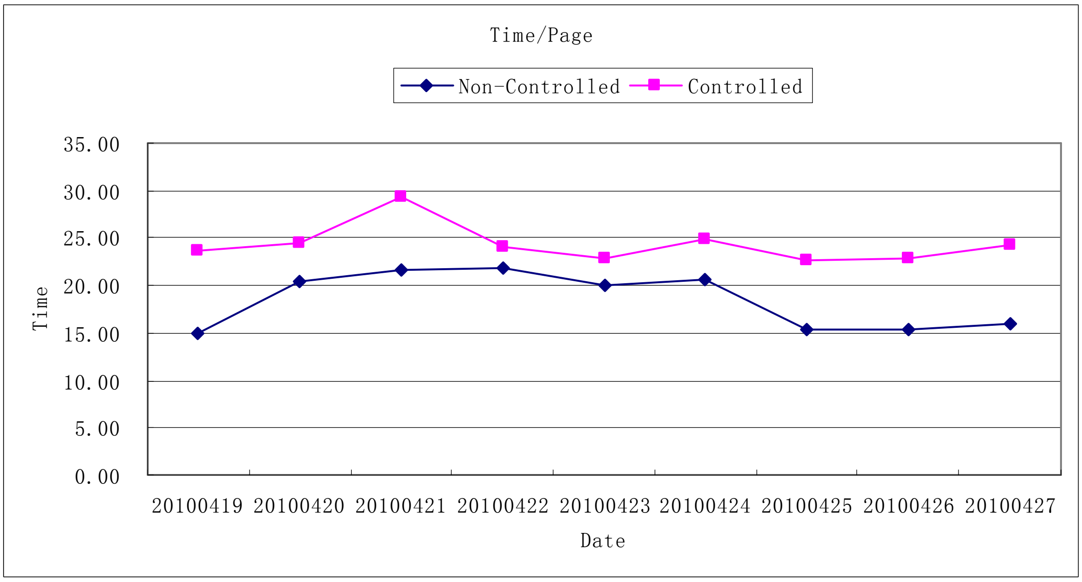


Fig. 5.11 Comparison of Time on each page between group (I) and group (II)

The results show that the proposed methods in this thesis may improve the usability rate of contents from web users. In other words, the users from controlled groups are more interested with their accessed contents.

5.3 Transcoding Mechanism

Transcoding model has many transcoders (also called media processor), each of which takes responsibility to transform one kind of media, such as video transcoder for video, image transcoder for image. After transcoding model has parsed the request (XML file) into R_{source}={<feature, value>}, feature $\in$Source of job and R_{target}={<feature, value>}, feature $\in$Target of job, which is sent by Adaptation Model, it submits the request to the related transcoder.

As we know, transcoding for each feature of learning media component takes time. In order to reduce the transcoding time, the transcoding model should choose a lowest cost state from cached contents to transcode according to feature finite state machine cached for accessed learning media component. The state in FFSM represents the feature and transcoding result, which is $s = < feature, result >$. The flowchart is shown in Fig. 5.12.

Set A and B are extracted from cached contents based on job requests. A minimum cost is chosen for transcoding.

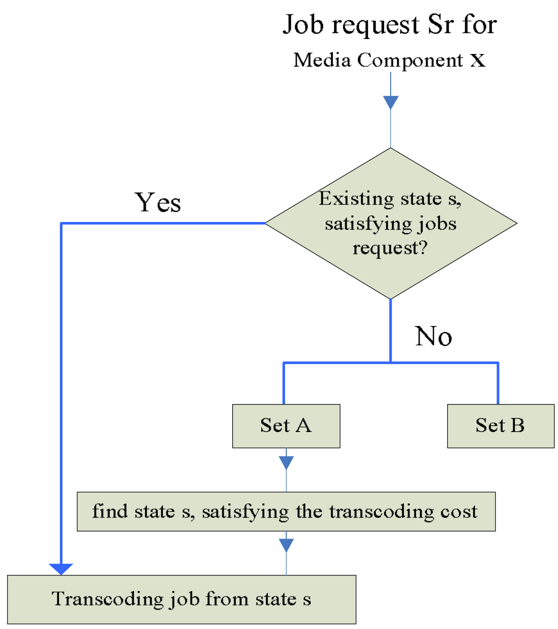


Fig. 5.12 Workflow for Transcoding

The system only transforms the different features between closest cached learning media component and requested target learning media component. It will reduce the response time for transcoding from closest or same cached learning media component. The transcoding procedure is divided into two steps: cache checking, and real-time transcoding realization.

Sr is the constrained feature of contents from request jobs. Set A and Set B are the higher Set and lower Set separately. Finally, the closest state s is chosen as the cached state for transcoding from Set A. In other words, s has most similar feature with Sr.

5.3.1 Cache Checking

The transcoder checks whether media satisfying request job already existing in the content cache server. This research uses Difference Value Operator (DVO) to judge where the system should transcode a learning media component based on cached learning media components.

Difference Value Operator $\oplus$ (c=a$\oplus$b):

$$c = a \oplus b = \begin{cases} 1, \text{a matches with b;} \\ 0, \text{a does not match with b;} \end{cases}$$

Table 5.13 Condition for Transcoding

if(DVO = 0)
then
transcode
else
Keep same

For example, learning media component is jpg image SO_l={jpg, size, name,…}, and device only supports gif format for image SO_d={gif, size, wml,…}, so DVO_{format} = a $\oplus$ b equals 0.

Table 5.14 Cache Matching Algorithm

Input
R; //Job request
Output
s; //State of transcoding
FFSM; // Feature Finite State Machine of content
Algorithm
if $R_{FFSM} = \phi$ *then create a initial state* $< feature, feature >$ *of FFSM*
for R_{source}*, which represents original feature of learning object;*
create a state set $s_{set} = \{s \mid s \otimes R_{t\arg et} \neq \phi, s \in S_{FFSM}\}$*;*
if $s_{set} = \phi$ *then* $s = s_1$
else
$\cos t = \{\cos t(c_s(s_{feature} \rightarrow R_{t\arg et}) \mid s \in S_{set})\}$
$s = Value\_\mathrm{Re}verse\_State(Min\{\cos t\})$*;*

5.3.2 Transcoding Realization

This step chooses suitable transcoder(s) to complete jobs according to $\mathrm{Re}verse\_Feature(s_r, s)$ by the following Formula.

$$\mathrm{Re}verse\_feature(s_r, s) =$$

$$\{< \mathrm{f_i}, \mathrm{w} > \mid f_i = S_r.f_i \text{ if } \mathrm{f_i} \in \mathrm{S_r}, \mathrm{f_i} \in \mathrm{S}, \mathrm{w} = 1 - \frac{\mathrm{f_{S_r.i}}}{\mathrm{f_{S.i}}} > \varepsilon\}$$

The transcoder accesses the original or transcoded contents and then recodes or reconstructs content into target contents, which are stored in content cache server. At last, transcoding responses are sent to Adaptation Model.

Table 5.15 Transcoding Algorithm

Input

s; //Job request

Output

S.result; //result of transcoding

FFSM; // Feature Finite State Machine of content

Algorithm

if $s \otimes R_{t\arg et} = \phi$ *then return s;*

$s_r = (R_{t\arg et}, null)$;

create one state transition $s \rightarrow s_r$ *in FFSM;*

$v = Rreverse\_feature(s_r, s)$;

switch(type of media)

case image: transform based on v;

case text : transform based on v;

case audio: transform based on v;

case video: transform based on v;

case document: transform based on v;

end switch

$s_{r \cdot result} = result(transcoding)$;

Table 5.16 Transcoding Jobs for Image

```
<?xml version="1.0" encoding="utf-8"?>
<transcodingJob>
  <jobID>M100101</jobID>
  <source>
    <contentType>image/jpeg</contentType>
    <location>source/send_mail.jpg</location>
  </source>
  <target>
    <transcodingParams>
      <image>
        <contentType>image/gif</contentType>
        <sizeLimit>30000</sizeLimit>
        <colorScheme>
          <scheme>True</scheme>
          <depth>24</depth>
        </colorScheme>
        <width>240</width>
        <depth>320</depth>
        <resizeDirective>AspectRatio</resizeDirective>
      </image>
    </transcodingParams>
  </target>
</transcodingJob>
```

Table 5.17 Transcoding Results for Image


```xml
<?xml version="1.0" encoding="utf-8"?>
<jobResult>
  <jobID>M100101</jobID>
  <mainReturnResult>
    <returnCode>2000</returnCode>
    <returnString>Success</returnString>
  </mainReturnResult>
  <duration>63</duration>
  <output>
    <contentType>image/gif</contentType>
    <location>tmp/send_mail_240_320.gif</location>
    <mediaSize>5023</mediaSize>
  </output>
</jobResult>
```


5.4 Evaluation on Adapted Contents

A so-called adaptation of learning contents modeling system proposed in this research is not an isolated system, rather easily combined with other e-learning system, which may get original contents from e-learning system and recommend adaptive contents according to learning context awareness: device feature, learner's preferences. These modules are independent units that interact with each other through e-Learning system. The distributed modular architecture of the adaptation platform ensures scalability. Well-defined interfaces based on open standards also guarantee interoperability and flexibility of freely adding, removing and migrating modules.

Another, the conversation theory suggests that learning to be successful requires continuous two-way conversations and interactions between the teacher/teacher and amongst the learners (Motiwalla, 2007). It is important for learners to share learning experience through online learning community or message boards (Chang, 2008; Farooq, Schafer, Rosson and Carroll, 2002; Robertson, Fuller, Midon, Smith, Sadera and Song, 2008). The teacher can guide the learning activities either through instant messaging or bulletin board system (BBS) (Ogata, 2008). Learner may response his/her feedback to teacher or other participants by BBS or instant messaging through his/her ubiquitous device (Bollen, Eimler, Hoppe, 2004).

Based on conversation theory, an Adaptive Ubiquitous Learning (AubiLearn) system has been developed to evaluate proposed methods, which allows learners not only to access adaptive contents, also to participate discussion by mobile mail/MMS/SMS. Utilized machines have the following hardware characteristics: Core 2 Duo E6600 2.40GHz FSB1066MHz with 1GB RAM and hard-disk of 320GB. Server is running a Windows XP(Apache, MYSQL, and PHP). To exploit the web transcoding service, this research uses the following open source for media transcoding:

1. ImageMagick for image (ImageMagick, 2009);
2. FFmpeg for video and audio (FFMPEG, 2009);
3. Microsoft Office API for standard document (Microsoft, 2009);
4. Microsoft Speech Development Kit 5.1.
5. Learning objects on AubiLearn are Chinese contents taken from cctv.com.

5.4.1 Adaptation on Image Contents

The image contents are evaluated in this part for learning discussion because the formats of image uploaded by learner's device are different.

The Fig.5.13 shows the transcoding response time for different image on one feature. The response time depends on more features, e.g. format, dimension, size.

The Fig.5.14 shows the transcoding ratio, transcoding time of an image contents (size: 18,580, and dimensions: 600x390) with different device features and network speed. The AubiLearn system could create different size and dimensions according to learning context. For poor wireless signal strength, the contents size will be compressed to 6.6% of original contents. Of course, the format of image learning object is recoded into suitable contents. It really consumes more time during the transcoding dynamically. On the contrary, for strong signal strength (PC learner), the AubiLearn system will send original contents for learners.

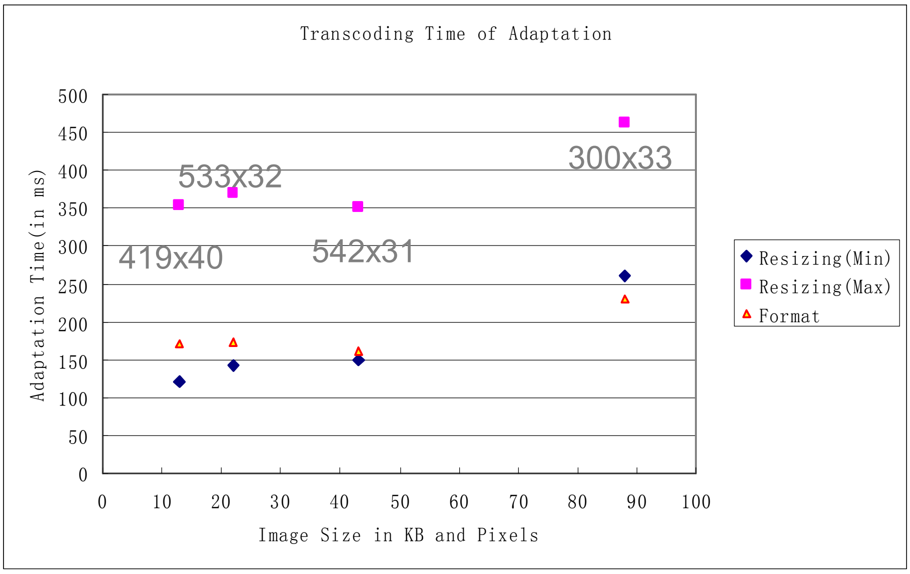


Fig. 5.13 Transcoding Time of Adaptation

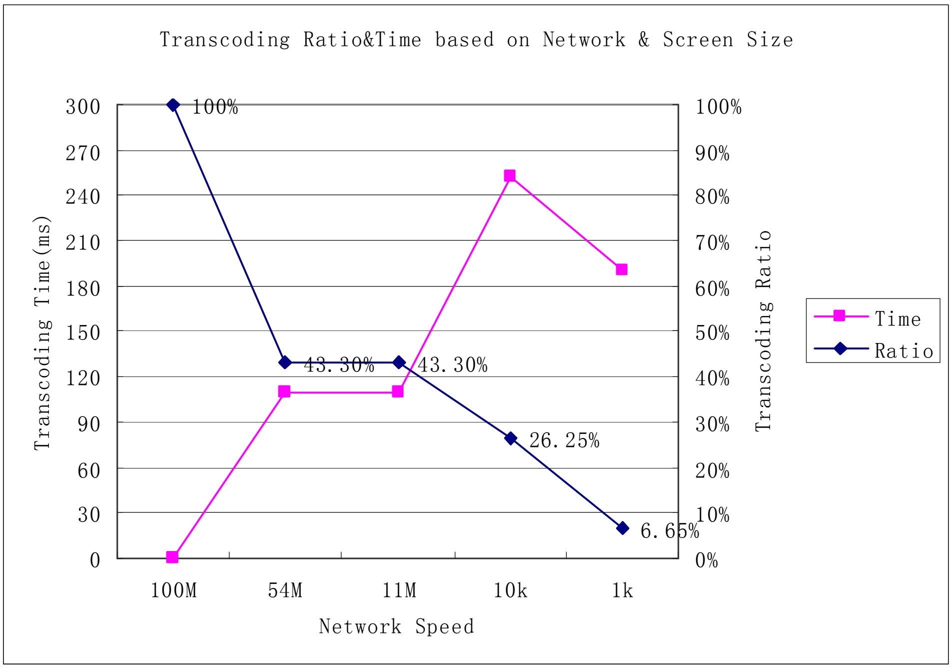


Fig. 5.14 Transcoding Ratio&Time based on Network & Screen Size

5.4.2 Adaptation on Document Contents

In general, standard documents contain plain text and images data. In the evaluation model, real learning objects with ppt standard document, which can not be displayed on ubiquitous device used at most times. When learner accesses a standard document: PowerPoint files, which may contain text, image, audio, animation and video, Adaptation Model recommends the personalized contents from a sub-page (one slide) based on learners preference and context awareness, such as deleting image (may not be favorable to learner) or audio (may not be supported by device). At last, some components of pages are recommended to Adaptation Model.

Adaptation Model creates adaptive contents according to learning context. Lastly, the adaptive contents may be based on image, web pages, voiceXML, MMS and so on. In this thesis， web pages and MMS/Mail/SMS are only discussed.

- **Adaptive contents based on MMS/Mail/SMS**

If device does not support a web browser, Adaptation Model only creates a transcoding request for text or limited media to transcoding Model by MMS/SMS. At last, delivery model pushes contents to learners in SMS (only text) or MMS/Mail (limited media contents). The Fig.5.15 shows the transcoding time for each request to standard contents, ppt files (size: 2125KB).

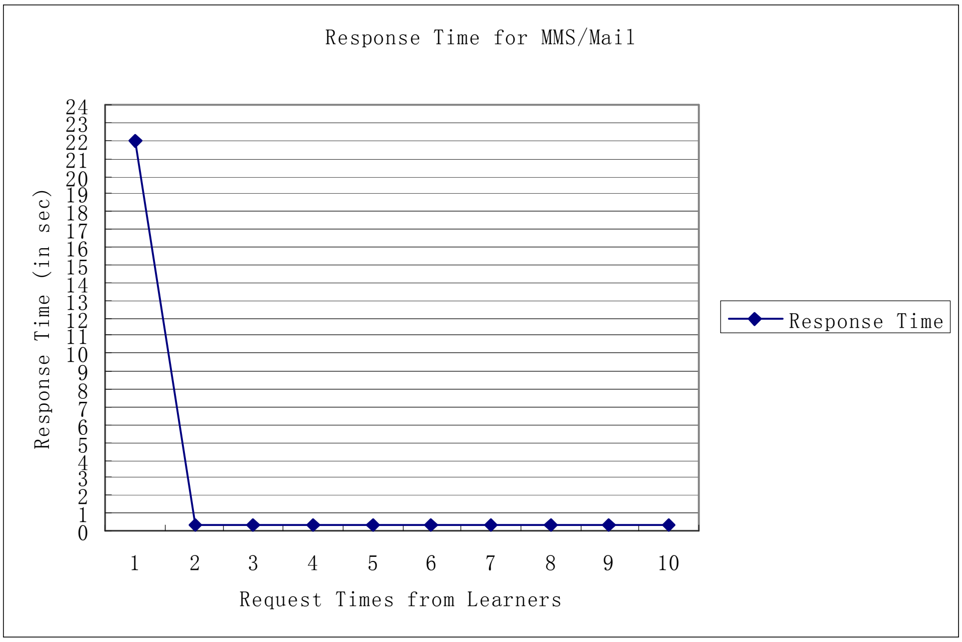


Fig. 5.15 Response Time for MMS/SMS/MAIL

From the Fig.5.15, we can know that it takes more time to response the learner's request at first time because the system extract the plain text and image data from ppt files. But it take few time to transcode from second time because it is not necessary to transcode the original contents. To different size and contents of ppt files, the response times are also increasing linearly. In general, the bigger, the more time and the more complex, the more time (Cardellini, Yu, Huang, 2000).

- **Adaptive Contents Based on Mobile Pages**

If a mobile browser is embedded in handheld device, delivery model negotiates components of personalized contents (sub-page) and sends a transcoding request for unsuitable media. Then, Markup Language Module creates adaptive a mobile page by replacing the HTML tags with mobile tags (such as cHTML, WML). Lastly, mobile page, video or audio content is pushed to the learner.

Fig.5.16 shows the response time for request from learners at first 150 requests. During each request, a dynamically transcoded content is added into FFSM, whose process consumes the time. At first, the response time is closer to n^2, meaning that new adapted content is inserted into cache server. At peak value, the response time is over 50 seconds. But after some request, the response time begins to reduce quickly and arrive at a steady value at last, which means that the contents accessed have been transcoded for all adaptive to learner's devices.

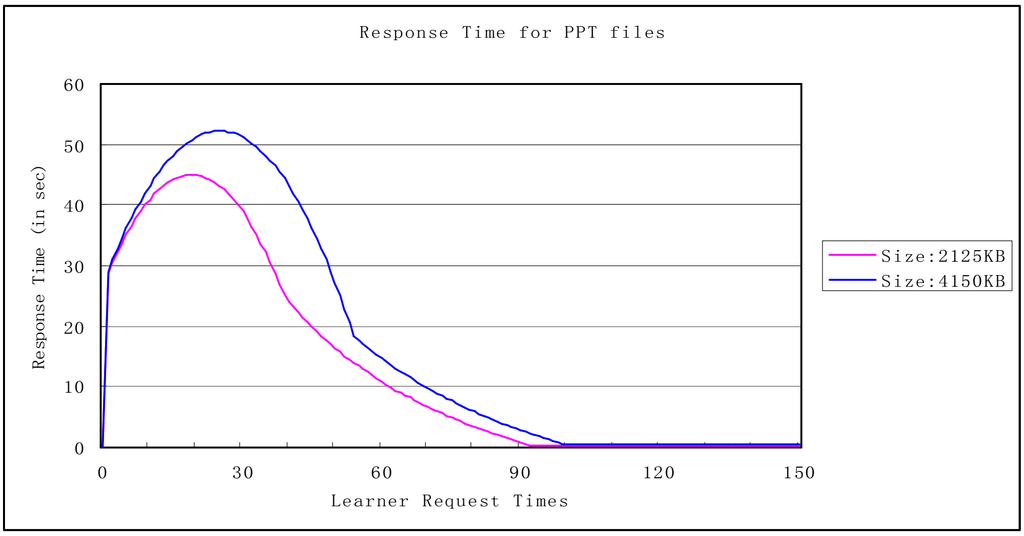


Fig. 5.16 Response Time for Mobile Pages

From Fig.5.16, the spatial consumption is increasing fast during the initial request from learners. But along with the steady of transcoding, the spatial consumption is also tending towards stability.

5.4.3 Adaptation on Rich Media Resources

The table 5.18 shows times for transformation of a specific media into another final media (Video with mpeg file 800X600, size of 4.12MB; text: 0.3KB). As reported in the table, times of transcoding vary from 0.7 seconds to 2.2 seconds. As to text, instead time to convert text into wav format, it takes more time to transcode at first time. But next time, to audio, time will need less time to transcode from wav to other audio format (e.g. amr only 706 msec). The results show that transcoding strategies can be applied on e-learning in real time. Also, it needs less transcoding time than those in Silvia(2007).

Table 5.18 Adaptation Time on Rich Video, Text, and Audio

Media	Original LO		Adapted LO		Time (ms)	
	Dimensions	Format	Dimensions	Format	Silvia, 2007	Proposal
Video	800X600	.mpg	240X320	.mpg	1856	1723
Video	800X600	.mpg	240X320	.3gp	2450	2200
text	NA	.txt	NA	.wav	2045	2045
audio	NA	.wav	NA	.amr	823	706

5.5 Evaluation on Learners

The aims of evaluation wished to discover if the students felt that they gained a better learning experience on for the proposed adaptation system, compared with how they felt prior learning experience, a questionnaire which involves fifteen questions divided into two types questions were designed to measure whether the adapted contents satisfy the real requirements of most learners. The two types of questions contain learner's information using mobile device and operation on AubiLearn, which is shown in Table 5.20. The contents are made for Learning Chinese on ubiquitous device. Some learning snapshots are shown in Fig. 5.17.

When the learner studies by their personal computer, the AubiLearn send original contents to them. For mobile device, the system creates adaptive contents. E.g.

1. *text(messy characters)→ correct text*
2. *text→audio*
3. *video→adapted video*

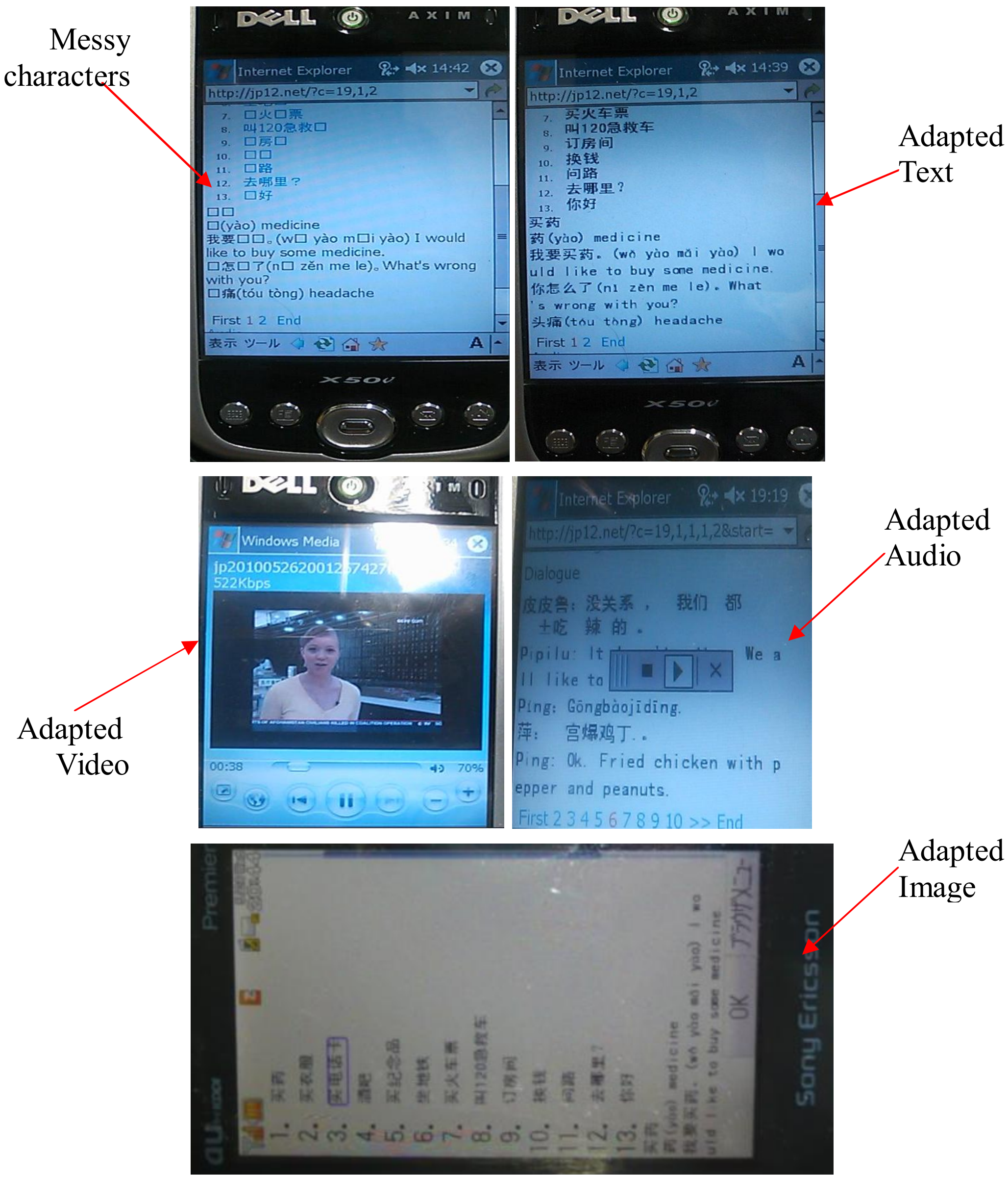
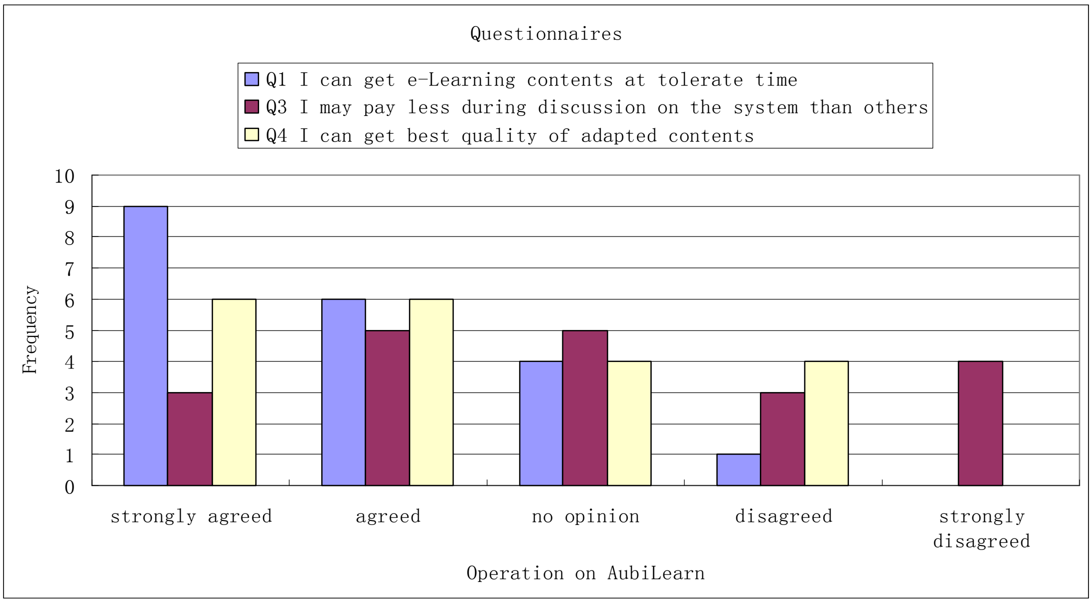
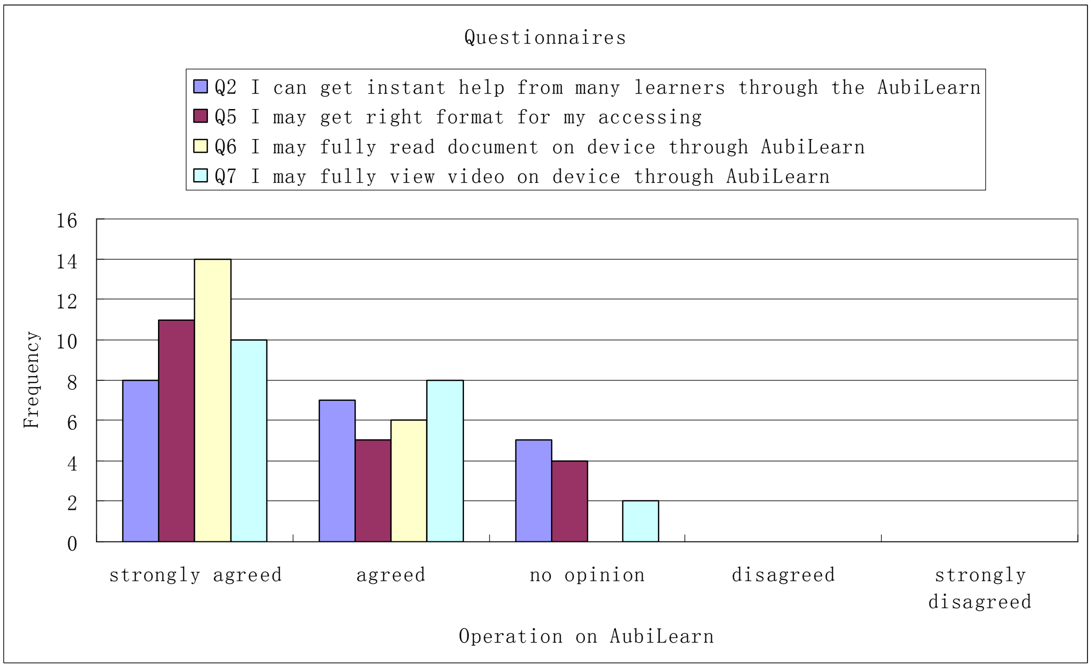


Fig. 5.17 AubiLearn System on Ubiquitous Device

The six questions are designed to know about the learning experience on ubiquitous device, shown in Table 5.21. None of them knew that they could study on ubiquitous device. Especially, they thought that it was not possible to read rich media on ubiquitous device, e.g. ppt, doc files etc. Another ten questions are designed to investigate about learning experience on AubiLearn system. Each question from the questionnaire will be presented, followed by a graphical representation of the results.





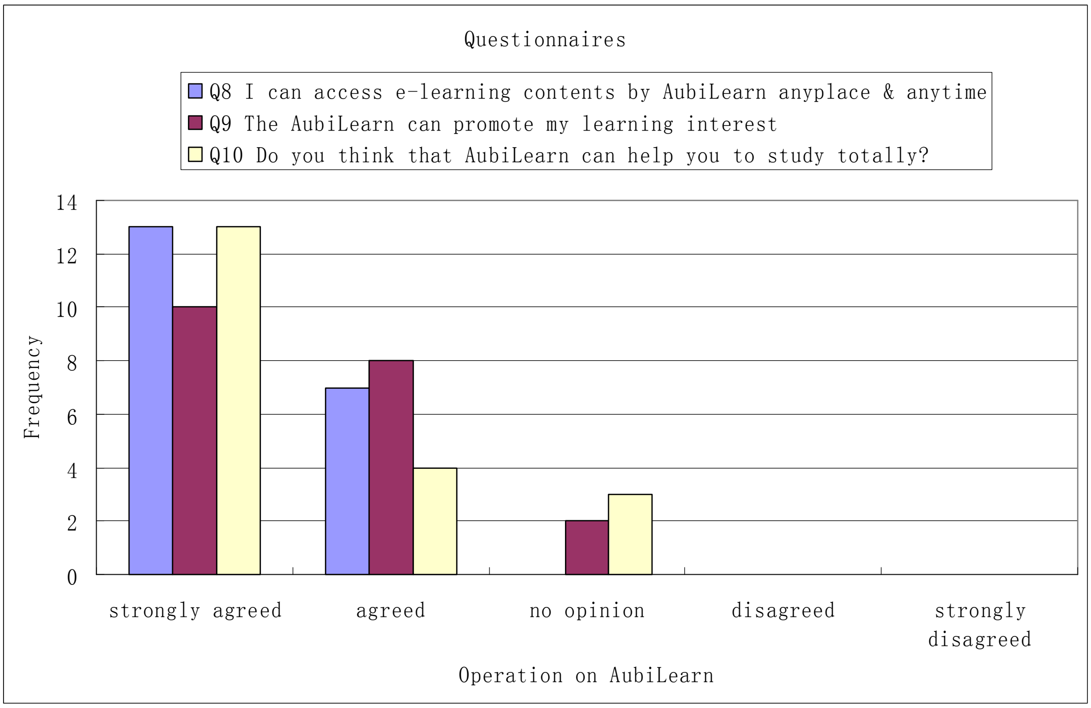


Fig. 5.18 Summarization of Questioners

The results in questionnaire show that the learners feel convenient and easy to use when they participate in the discussion by their mobile device. 79.50% attendees give a positive response to the use experience of AubiLearn system. Before the use of AubiLearn, no one of attendees responds that learners can view standard documents on mobile device. But 100% attendees agree that documents can be displayed on mobile device. Also, all adapted videos content can be displayed on each attendee. 80% among attendees think that AubiLearn may improve learning interest by providing a seamless learning environment.

Table 5.19 shows that all features in the AuviLearn for learners are rated as very important as 8 weighted average values (WAV) obtained are above 3.00. Announcement, *I can access e-learning contents by AubiLearn anyplace & anytime* is rated the highest among them with 3.65 point. A mean value of 3.2 shows adaptation method is a very important for ubiquitous learning environment.

Of course, we also find that the most issue existing is the QoS of adapted contents (WAV: 2.7) because of the limited features of ubiquitous device. For example, the caption of video is not clear after the high resolution video is re-encoded. At this situation, the learner studies by listening. Till now, we can not resolve these questions because of the device hardware. Another question, it is the communication fees (WAV: 2). Through the question 3, half of them pay more to access the learning contents for study. Fortunately, some companies allow users to choose a cheap fee plan for internet, e.g. max internet use. We think that it must be cheap for learners to study on ubiquitous device in future.

Table 5.19 Importance of Each Feature to Learning Experience

NO	Questionnaires(0:strongly disagreed-scale-4:strongly agreed)	WAV
1	I can get e-Learning contents at tolerate time	3.15
2	I can get instant help from many learners through the AubiLearn	3.15
3	I may pay less during discussion on the system than others	2
4	I can get best quality of adapted contents	2.7
5	I may get right format for my accessing	3.35
6	I may fully read document on device through AubiLearn	3.7
7	I may fully view video on device through AubiLearn	3.4
8	I can access e-learning contents by AubiLearn anyplace & anytime	3.65
9	The AubiLearn can promote my learning interest	3.4
10	Do you think that AubiLearn can help you to study totally?	3.5

Weight Average Value (WAV)=(P+2Q+3R+4S)/20,
where P, Q, R, S are the number of responses for the Likert Scale 1,2,3,4 respectively and 20 is the total number of responses.

5.6 Summary

This chapter mainly explains the realization of adaptation contents. Firstly, a MQ-RP(Multiple-Response Reward-Penalize) algorithm is proposed to recommend the preferred media type. According to constrained features of feature finite state machine created by negotiation method, adaptation methods suggests the constrained version of learning media components for accessed learning media components. At last, the transcoding realizing algorithm and caching methods are proposed to improve the transcoding features.

Also, the proposed adaptation technologies are also evaluated in this chapter. The four issues considered are mainly discussed: performance to ubiquitous environment, response time, computing resource, and learning experience. Through this research, the accessed contents may be recoded according to learning environment dynamically. It is not necessary to create all adapted contents by LMS managers. Also, the adaptation process not only need few computing resource, also completes the learning requests in a tolerate time. The system can provide a seamless learning for learners. The evaluation results show that learning experience is improved.

Next chapter will concludes the thesis and summarize the contributions of this research. Also, future works are sketched in next chapter.

Table 5.20 The Descriptions of Questions Types

Question Type	Number of Questions	Description
Learner’s information using mobile device	6	To know about learner’s information
Operation on AubiLearn	10	To know about learner’s operation and quality of adaptive learning contents

Table 5.21 Results of Learner’s Information (Number: Count of Learners)

Question	Yes	No
Do you have mobile device	20	0
Have you ever accessed learning contents by your device	0	20
Have you ever used your device for discussion (mms, mail, bbs)	20	0
Have you ever got help from many participants at same time	8	12
Have you ever accessed e-Learning on your mobile device	0	20
Do you think documents (ppt, word, pdf etc) can be read on mobile device	0	20

Chapter 6

Summary and Outlook

Objectives

This chapter includes:

- Concluding Remarks Concerning the Whole Thesis
- Extending the Proposed Methods for Further Research

Overview

This chapter aims at summarizing most relevant finding and contributions on the research discussed in this thesis. First, the main contributions of this thesis concerning the questions addressed are given. Last, this chapter finalizes with giving an outlook for future work.

6.1 Main Contributions

The basic hypothesis of this research stipulated in chapter 1 is that introducing adaptation mechanisms into e-learning services can improve the usability of e-learning contents on ubiquitous device. The research in this thesis has concentrated on the issues of designing and implementing learning system that should meet the learning context awareness in ubiquitous learning environment expendably.

6.1.1 General Research Goals

1. ***How to get the* capabilities *of ubiquitous device in the running***

In general, a device database adopted by the WURFL (2007) model is used to define and update device profiles for learners. Besides the mobile device repository, the capabilities of mobile browsers have also been updated in this research. According to repositories of mobile device and browser, a detection method proposed in section 4.3 uses all headers to recommend closest capabilities of mobile device.

2. ***How to reason the*** **context** ***to create adaptive contents according to learner's context*** **awareness**

Regarding the integration of duties between context awareness and learning needs, a general contextual module has been presented in section 5.2.1 based on the definition of ubiquitous learning state in section 3.2.2. What final format of original learning media component used first is ranked in section 5.2.1. From this point of view and as result of the theoretical investigation, the learning contents adaptive to learning context have been derived and implemented in section 5.2.4.

3. ***How to*** **transcode** ***original contents into adaptive contents according to context awareness***

The proposed Feature Finite State Machine (FFSM) as well as the proposed adaptation architecture has enabled the negotiation of contents transparently in section 5.2.2 and 5.3. Situational module creates a FFSM for each of learning media components according to learning context (preferred media type, learning media component, network features, and device capabilities) in section 5.2.2. Each FFSM represents the transition feature of learning media component corresponding to ubiquitous device.

At last, a job-based solution approach in a flexible and reusable architecture is enabled to realize the real transcoding task in section 5.2.3. The adaptation evaluations in section 5.2.4, 5.4.1, 5.4.2, 5.4.3, 5.5 show that the adaptation performance is better matched with learning contexts.

6.1.2 Special Research Questions

1. ***How is*** **possible** ***to detect the feature of mobile device when there is no***

information in database

A new method proposed in section 4.3 uses device, browser and all contexts from ubiquitous device for detection. It is implemented by an enhanced technique. The detection result compared with general methods is shown in section 4.3.3. The test results show that the method of detection proposed can get a better performance than other general methods.

2. ***How is possible to transcode the learning contents on the fly***

In accordance to the learning object sharing a same FFSM structure, a caching technology has been developed and implemented to decrease the consumptions of time for dynamical transcoding of learning contents. The transcoding time quickly reduces along with the request times specially.

Another, the contextual and situational modules according to PPS system create adaptive contents according to learning context-aware. The adaptive decision interpreter can get the conclusion under few states. The state spaces are reduced because of cross-use of state. It is also exploited as a reasonably efficient mechanism for performing highly combinatorial evaluations among ffsm state where large numbers of joins must be performed between fact tuples. Also, it may avoid the bottle-neck question for a transcoding peak.

3. ***How can the system framework create scalable adaptive contents for ubiquitous learning, which is implemented on an adaptive behavior according to learning context awareness***

A so-called adaptation of learning contents modeling system proposed in chapter 3 is not an isolated system, rather easily combined with general e-learning system, which may get original contents from e-learning system and recommend adaptive contents according to learning context awareness: device feature, learner's preferences, et al. These modules are independent units that interact with each other through e-Learning system. The distributed modular architecture of the adaptation platform ensures scalability. Well-defined interfaces based on open standards also guarantee interoperability and flexibility of freely adding, removing and migrating modules.

6.2 Open Issues and the Road Ahead

The architecture and concept proposed in chapter 3 and the application of the adaptation developed in chapter 4, 5 have introduced a broader view of cartography for ubiquitous learning environment. Nevertheless, both the architecture and the adaptation are still far from being exhaustive and can be refined in many dimensions.

1. Undoubtedly, the specific research question concerning “types of contextual information and sources” using in ubiquitous learning environment represents the first and main open issue. Although the system may sense or detect over 90% contexts from learners (Tenla, 2008), it is still challenging works 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 mobility.

2. Content adaptation is required to provide a universal access from e-learning content provider or the internet by and ubiquitous device. The adapted contents should be maximizing the learner Quality of Experience (QoE). The system should decide how to react while learning context is changing and select the appropriate adaptation and service parameters, e.g. adaptation authorization (Vitor and Maria, 2009).

3. Interactions among participants during ubiquitous learning environment are another open issue now. Learning to be successful requires continuous two-way conversations and interactions between the teacher/teacher and amongst the learners (Motiwalla, 2007). It is still difficult to realize more complicated interoperation on constrained devices today.

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List of Publications

■ Papers in Journals

1. **X.Y. Zhao**, T. Okamoto. Adaptive multimedia content delivery for context-aware u-Learning. *International Journal Mobile Learning and Organisation* (ISSN: 1746-725X). *(Accepted)*. (Related to the Chapter 5)

2. **X.Y. Zhao**, T. Okamoto. Scalable Learning Contents for Virtual Community in a Context-Aware Environment. *IEEE Multidisciplinary Engineering Education Magazine* (ISSN: 1558-7908). 2009(6), 4(1):37-45. (Related to the Chapter 4 and 5)

3. **X.Y. Zhao**, T. Ninomiya, M. Vilenius, F. Anma, T. Okamoto. Adaptive Content Delivery System for Ubiquitous Learning. *The Journal of Information and Systems in Education* (ISSN: 1348-236X). 2008(12), 7(1): 95-102. (Related to the Chapter 4)

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4. **X.Y. Zhao**, X. Wan, T. Okamoto. Adaptive Content Delivery in Ubiquitous Learning Environment. *The 6th IEEE International Conference on Wireless, Mobile and Ubiquitous Technologies in Education* (IEEE WMUTE 2010). 2010(4)：19 - 26. (Related to the Chapter 3 and 5)

5. **X.Y. Zhao**, T. Ninomiya, F. Anma, T. Okamoto. A Context-Aware Prototype System for Adaptive Learning Content in Ubiquitous Environment. *2008 IEEE International Symposium on IT in Medicine & Education* (ITME 2008). 2008(12):164-168. (Related to the Chapter 2 and 4)

6. **X.Y. Zhao**, T. Ninomiya, F. Anma, T. Okamoto. Adaptive and Personalized Content Architecture for Mobile Learning System. *The 11th IASTED International Conference on Computers and Advanced Technology in Education* (CATE2008). 2008(10):26-31. (Related to the Chapter 3 and 5)

7. **X.Y. Zhao**, T. Okamoto. Device-Independent System Architecture for Adaptive Mobile Learning. *The 8th IEEE International Conference on Advanced Learning Technologies* (ICALT'08), 2008(7):23-25. (Related to the Chapter 3)

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8. **X.Y. Zhao**, T. Okamoto. A Personalized Mobile Mathematics Tutoring System for Primary Education. *The Journal of the Research Center for Educational Technology* (ISSN: 1948-075X). 2008(4), 4(1): 61-67.
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10. X. Wan, Q. Jamaliding, **X.Y. Zhao**, F. Anma, T. Okamoto. Using comprehension degree to improve the quality of recommender system for group learning support. *The 2nd International Workshop on Education Technology and Computer Science (ETCS2010)*. 2010(3): 3-6 (V.II).
11. **X.Y. Zhao**, T. Okamoto. An Email-Based Discussion Learning System with Ubiquitous Device Support. 2009 *The 4th International Conference on Computer Science & Education* (ICCSE 2009). 2009(7): 1420-1424.
12. **X.Y. Zhao**, X. Wan, T. Okamoto. A Recommendation System Based on Unavailable Items Cached from Searching Engine. 2009 Rakuten Research & Development Symposium. 2009(11):77-80
13. **X.Y. Zhao**, N. Nagata, T. Okamoto. Adaptive Discussion System for Ubiquitous Learners. *The 5th National Research Meeting of Japanese Society for Information and System in Education*. 2009(1), 23(5): 56-59.
14. **X.Y. Zhao**, T. Okamoto. An Adaptive Mobile Mathematics Tutoring System for Young Children. *The 33rd Conference of Japanese Society for Information and System in Education* (JSiSE2008). 2008(9):158-159.
15. **X.Y. Zhao**, T. Okamoto. A sharing content model for mobile learners. *The 32nd Conference of Japanese Society for Information and System in Education* (JSiSE2007). 2007(9):146-147.

■ Awards

16. **BEST Ph.D. STUDENT AWARD**. Issued by *The International Association of Science and Technology for Development (IASTED)* at The 11th IASTED International Conference on Computers and Advanced Technology in Education (CATE2008) on Sep. 30, 2008 at Crete, Greece.

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