

The Dynamic Web Services Adaptation Framework in Context-Aware Mobile Cloud Learning Using Semantic-Based Method



Sufri Muhammad, Novia Admodisastro, Hafeez Osman, Norhayati Mohd Ali

Abstract: Most of Service-Based Applications (SBAs) have to be changed after their first deployment not solely due to the changing system requirements as well as of continuous change of the environment itself. With the growth of web service paradigm, there is a need for an efficient mechanism in dynamic adaptation process to offer users a better service experience. In particular, context-aware can be adapted in dynamic adaptation by considering user's contexts and device's contexts. Context awareness will be a key area for Mobile Cloud Learning (MCL) environment as it helps in the reasoning process to provide correct education resources for learners' prospect. Contextual information are represented using semantic-based approach for high expressiveness and formal representation for reasoning technique. However, dynamic adaptations frameworks in previous research are still lacking in terms of contextual information of the learner and device, and quality of services (QoS) were not considered. Besides, there is limited support of semantic expressiveness in terms of contextual information and services by using solely semantic-based technique. This paper proposes Dynamic Adaptation in Context Aware Mobile Cloud Learning (DACAMoL) framework to support adaptation process in MCL using semantic-based approach. The framework is applied in MCL mobile application that offers basic learning language.

Keywords: Dynamic Reconfiguration, Adaptation, Context-Aware, Services Adaptation

I. INTRODUCTION

The initiation of self-adaptation techniques helps to tackle the system complexity that is executed in their environment. Some services may require an appropriate environment to be operated successfully. As the environment changes and new context-aware are sensed, the current services are unable to be executed to obtain the correct result. Hence, they should be replaced with other equivalence services. Dynamic service adaptation in context-aware environment has become one of the major research trends in service-oriented systems.

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* Correspondence Author

Sufri Muhammad, Faculty of Computer Science & Information Technology Universiti Putra Malaysia 43400 UPM Serdang Selangor, Malaysia

Novia Admodisastro, Faculty of Computer Science & Information Technology Universiti Putra Malaysia 43400 UPM Serdang Selangor, Malaysia

Hafeez Osman, Faculty of Computer Science & Information Technology Universiti Putra Malaysia 43400 UPM Serdang Selangor, Malaysia

Norhayati Mohd Ali, Faculty of Computer Science & Information Technology Universiti Putra Malaysia 43400 UPM Serdang Selangor, Malaysia

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Context awareness enables the system to sense and react with their physical environments such as connectivity, location, and device status and user preferences. This capability is substantial in pervasive environment where right resources to serve the users is based on the perceived contexts. The process of finding the right services is called dynamic adaptation process. Dynamic adaptation is a substitution and modification of services during runtime for system upgrading or new requirement from the user.

According to Berners-Lee et al. (2001), the semantic-based approach is one of the promising methods to support the reasoning process in dynamic adaptation. Semantic-based adaptation represents the context using a well-defined meaning and formal representation using ontology, Nacer & Aissani (2014). Semantic-based approach has been used in many domains to support the adaptation process however, our observation show that this approach has less attention from academia and industry in the context-aware mobile cloud learning environment. One of the challenges encountered in this research is the semantic-based approach provides limited support of context representation of the services and context for reasoning process if only one technique has been used. Whereas the combination of the techniques in semantic-based approach enriches the context representation of the services and contexts during the reasoning process to find the equivalence services, Harchay et al. (2015), Gomez et al. (2014). Apart from that, learners can get easily distracted if it takes a long time to load and display the learning content, Gurung et al. (2016), Wang et al. (2016). Hence, there is a need to consider the network status, battery level, and QoS in terms of their services availability and reputation to retrieve the Learning Resources (LRs) (Wang et al., 2014). The other challenge is the correctness of the service adaptation in order to get the most equivalent service to be replaced which should act in accordance with the context changes, Gao et al. (2015). Based on research done by Kolikant (2005), correctness in professional definition is as follows: "a program is considered as a working program if it exhibits correct I/O behaviour for all input in the domain of the problems space". Thus, this paper is intended to solve these challenges by devising a comprehensive dynamic service adaptation framework in context-aware mobile cloud learning using semantic-based approach that allow for systematic reasoning with contextual information and QoS. The framework also considers the usage of ontology and rule-based solution in



the dynamic web services adaptation. The rest of the paper is organized as follows: Section 2 describes the background and motivation. The proposed framework is explained in Section 3. Section 4 discusses the case study and evaluation, and finally Section 5 provides the conclusion for the paper.

II. BACKGROUND AND MOTIVATION

This section describes dynamic adaptation, context-aware and motivation of this research. Dynamic adaptation of services is operated during system runtime. This process is important since the system will continuously operate without any human intervention and no interruption whenever new requirements or change in users' context comes in. The adaptation process should consider user requirement and QoS as it is crucial for services discovery and services selection. One of the purposes to support dynamic adaptation is so that the system is aware of changes in terms of context, Alferez et al. (2014). Semantic-based approaches for dynamic adaptation in context-aware system have been discussed among researchers and developers, and they can be divided into several techniques which are Ontology-Based Solution, Rule-Based Reasoning, Middleware Solution, Code-Level approach, Model-Driven approach, and Message Interception, Peinado et al. (2015). Thus, the contextual information and QoS aspect are semantically mapped with the ontology for discovery and selection of services in context-aware environment.

Context-aware system has been considered in many domains such as e-health, e-commerce, e-learning and other. Mobile Cloud Learning is one of the domains that applied context-aware system. Context-aware mobile cloud learning is the ability of mobile learning application to connect to network access and being aware of contextual information from device, people, or surrounding, Wang et al. (2016). The context of this research is formally defined as "any information to describe entity's situation which the entity can be a place, person or object between a user and application themselves", Dey & Abowd (1999). Thus, the purpose of considering learner and device contexts helps in providing personalized learning resources according to individual preference and performance. Wang et al. (2016) in their research mentioned that the MCL system comprises four recursive services which are learning, assessment, communication, and analysis. These services have direct impacts on student learning experience and performance.

MCL is a growing research area that is becoming an important role to provide learners with personalized and adaptive learning resources according to their contextual information via their mobile devices. Contextual information is an important factor for achieving adaptive and personalized mobile cloud learning as it provides meaningful information on the device and learner status and behaviour, Gomez et al. (2014). To ensure learners are getting the correct substitution to the unavailable service, service adaptation process needs to consider internet connectivity, device's battery status, learner's preferences, and QoS. Thus, this resulted in our motivation to propose a dynamic adaptation framework in context-aware mobile cloud learning environment that should be adaptable

according to the user requests and their contextual information.

III. THE DACAMoL

The framework of Dynamic Adaptation of Context Aware Mobile Cloud Learning (DACAMoL), Muhammad et al. (2018) is presented in Figure 1. It is designed based on runtime environment to sense the device's context and learner's context through a mobile device for providing specific learning resources. As depicted in the framework, the mobile device is used as a front-end that captures any changes of contextual information such as learner's input, learner profile, network status, and device status. These contexts are stored in the specific local repository and then integrated with Dynamic Adaptation Management.

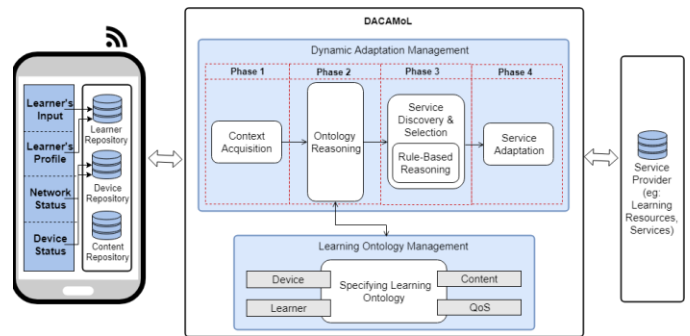


Fig. 1 Dynamic Adaptation of Context Aware Mobile Cloud Learning (DACAMoL) Framework

Dynamic Adaptation Management consists of four subsequent phases. Each of the phases is responsible for providing the correct learning resources starting from context acquisition, context centric adaptation, ontology reasoning, service discovery as well as rule-based reasoning. Ontology reasoning phase refers to Learning Ontology Management that specifies related knowledge on learning properties. These phases are described below.

Phase 1 (Context Acquisition)

This is a phase for acquiring the contextual information that are sensed automatically or manually provided by learner. This contextual information is acquired from the front-end and stored to a specific local repository. Table 1 shows context elements that are captured, their data instance, and data storage.

Table. 1 The required contextual information

| Context Element | Data Instance | Data Storage |
|-----------------|-------------------------|--------------------|
| Learner profile | String: {age, language} | Learner repository |
| Learner Input | Integer Mark: 0 to 100 | Learner repository |

| | | |
|----------------|---|-------------------|
| Network Status | String: {strong, poor} | Device repository |
| Device Status | Low level context to high level context (Battery level) String: {low, medium, high, full, charging} | Device repository |

Based on Table 1, data instance for device status contextual element are captured from low-level context and then converted to high-level context. This conversion is important to simplify the complexity of the rules and structured in a systematic way. This conversion from low level context to high level context is shown in Table 2.

Table. 2 Conversion from low-level context to high-level context

| Low-Level Context | Rule | High-Level Context |
|-------------------|--|--------------------|
| LowC | <pre>int contextValue = getContext(LowC) if X == contextValue(true){ HighC = convertContext } Return HighC //X defined by the user</pre> | HighC |

This contextual information need to be transformed into meaningful information. A number of different semantic technologies are used to transform such information. For example in DACAMoL, Ontology Web Language Sematic (OWLS) is used to transform learner profile contextual information as shown in Figure 2.

```
<?xml version="1.0"?>
<rdf:RDF>
<owl:DatatypeProperty rdf:ID="Learner_Profile_Name">
  <rdfs:domain rdf:resource="#Learner_Profile"/>
  Learner_Profile_Name_Data
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:ID="Learner_Profile_Age">
  <rdfs:domain rdf:resource="#Learner_Profile"/>
  Learner_Profile_Age_Data
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:ID="Learner_Profile_Language">
  <rdfs:domain rdf:resource="#Learner_Profile"/>
  Learner_Profile_Language_Data
</owl:DatatypeProperty>

<owl:DatatypeProperty rdf:ID="Availability">
  <rdfs:domain rdf:resource="#QoS_Constraints"/>
  99%
</owl:DatatypeProperty>
</rdf:RDF>
```

Fig. 2 Context representation using OWLS – Learner Profile example

Phase 2 (Ontology Reasoning)

As context is transformed semantically in phase 1, those contexts are mapped with Learning Ontology Management. Figure 3b shows DACAMoL ontology that describes learner and device specification which is adapted based on British

educational ontology, Casals et al. (2017). This hierarchical concept shows the relationship between contexts.

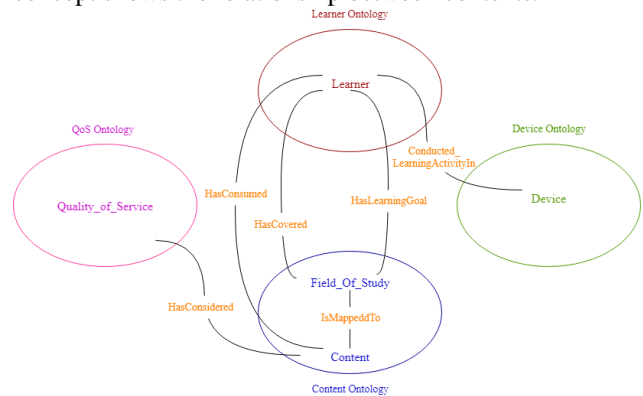


Fig. 3 a. DACAMoL Upper Ontology

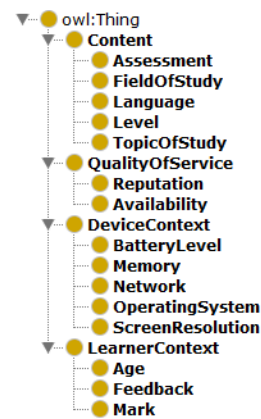


Fig. 3 b. DACAMoL Ontology (Protégé)

Context information is defined using upper ontology (refer Figure 3a) space that comprises one domain ontology which is Content Ontology used to define the subject of domain of interest. While three other sub-ontologies, QoS Ontology, Learner Ontology and Device Ontology are blended along with properties that are linked together with Content Ontology to form upper ontology space. These ontologies are then expressed in terms of hierarchy order that describes their relationship among classes. The field_of_study class has *HasLearningGoal* and *HasCovered* properties which associate with learner class that are useful to retrieve their learning goals and subject they covered. Content class associates with level class as well as topicofstudy class through *DependOn* property. The Level of the Content depends on learner’s as it associates through *DependOn* property. Mark is associated with Content through *DependOn* property since learner’s content depend on their mark. Content class is associated with learner class along with *HasConsumed* property that will define whether the learner has learned the specific content or not.

Learner ontology consists of learner class associated with content class and field_of_study class via *HasConsumed*, *HasLearningGoal*, and *HasCovered* properties. Learner information which is age captured through data property *HasAge* in string format. Mark class is associated with learner class which describes learner’s mark through *HasGain* object property.



Learner class is also associated with Feedback class through *HasProvided* property that describes learner's feedback.

Device ontology is used to capture contextual data about learner's device. The context is useful for discovery of learning content to match the characteristics of device used. The characteristics of the device that are relevant include available memory, battery level, and screen resolution (screen width with screen length).

The other ontology is QoS ontology. This ontology is used to capture data on Quality of Service which are availability and reputation. This data is important for ranking the candidate of service before selecting the best service to be adapted. The data type of the QoS values are in Integer. Class QoS is associates with class content through *HasConsidered* property.

Phase 3 (Service Discovery and Selection)

Mapping result from Phase 2 will be used in Service Discovery and Selection component to search any available and equivalence LRs from Service Repository. The discovery process browses available LRs from repositories according to the context representation, functional requirements and QoS. The discovery process uses Rule-Based approach to find available LRs from repository. After pull all available and equivalence contents from repository, rule-based approach that consists of if-then-else rules is used to rank the LRs according to their QoS. This process aims to come out with suitable LRs to meet learners' needs based on their contextual parameters. Three different rules; Rule 1 (service discovery rule), Rule 2 (service selection rule), Rule 3 (service enactment rule) is expressed in Table 3.

Table. 3 Rules for Service Discovery and Selection

| Rule | Description |
|-------------------------------------|--|
| <i>Rule 1 : Service Discovery</i> | Rule 1 uses to discover available services based on context changes from learner or device such as learner's age, mark, device's network or battery level. |
| <i>Rule 1.1</i> | Age = 7, 8, 9, 10, 11, 12 If Age = 7 8 9 10 11 12 Then Service = [Learning_Resources] |
| <i>Rule 1.2</i> | Mark = 0 to 100 If 0 ≤ Mark ≤ 100 Then Service = [AssessmentLevel 1] else if 80 ≤ Mark Level ≤ 100 Then Service = [Assessment Level 1, Level 2] else if 80 ≤ Mark Level 2 ≤ 100 Then Service = [Assessment Level 1, Level 2, Level 3] |
| <i>Rule 1.3</i> | Network = strong connection or poor connection If Network_strong ≥ 67 Kbps Then Service = [Assessment Level 1, Level 2, Level 3 with colour image] else If Network_poor ≤ 66 Kbps Then Service = [Assessment Level 1, Level 2, Level 3 greyed out image/textual] |
| <i>Rule 2 : Select Best Service</i> | Rule 2 uses to select best service from service candidate according to QoS values |
| <i>Rule 2.1</i> | If (QoSValue_Availability ≥ 98%) && (4 ≤ QoSValue_Reputation ≤ 5) Then Service = [Assessment Level 1, Level 2, Level 3 with colour image] else Then Service = [Assessment Level 1, Level 2, Level 3 greyed out image/textual] |
| <i>Rule 3 : Service Enaction</i> | Rule 3 uses to enact the adaptation |
| <i>Rule 3.1</i> | If Rule2.1 success Then Service = [Assessment Level 1, Level 2, Level 3] |

Phase 4 (Service Adaptation)

There will be a specific adaptation decision for respective context changes. Learning Resources (LRs) will be given to specific age, and assessment questions are given based on their marks. For example, Level 1 will always be displayed. Level 2 will be displayed if learner achieved 80 marks or above in the previous level which is Level 1. Level 3 will be displayed when learner scores 80 marks or higher for Level 2. Network status is categorized into two different scales which are Strong and Poor. According to Benlamri and Zhang (2014), network is considered as poor if it is 66 Kbps and below. Any value higher than this is considered as Strong network. Apart from that, battery level is considered

low if the value is 49% and below (Muhammad et al., 2018). Thus, Strong network and high battery level will let the LRs be displayed with image; whereas Poor network with lower battery level will display greyed out image or only display textual information depending on the QoS value. As Sommerville (2010) mentioned in his book, low battery could lead to device and system failure. Thus, this context change is important for battery saving purposes. LRs will be displayed with image if device's battery level is high or plugged, whereas LRs will not display any image if the battery level is low.

IV. DISCUSSION AND CONCLUSION

Evaluations of the framework are conducted using a case study. We present an exemplary educational scenario in a mobile cloud learning environment that considers contextual information from learner and device as well as QoS (i.e. availability and reputation) in their adaptation process. It is a mobile application for primary school students to learn the basic concepts in a specific language named *Mudahnya BM.*, an Android based application that follows MCL recursive model from Gurung et al. (2016) and Wang et al. (2016) that comprises four main elements which are learning, assessment, feedback, and performance. This application considers learner contexts such as their age and mark, whereas device context that have been considered are network status and battery level. QoS is also considered such as their availability and reputation. This mobile application, *Mudahnya BM* is integrated with DACAMoL framework via Representational State Transfer (RESTful) web service which can be accessed through Uniform Resource Identifiers (URIs). To operate the application, the device needs to have internet connectivity via Wi-Fi or any communication service provider.

In this work, a comprehensive knowledge on dynamic service adaptation framework for context aware in mobile cloud learning using ontology technique and rule-based technique in semantic-based approach are presented. Device and learner contextual information as well as, QoS in terms of availability and reputation are considered in services discovery and selection. An intended evaluation that will be performed on a specific case study is briefly described.

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