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A Data Fusion Approach to Context-Aware Service Delivery in Heterogeneous Network Environments

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Abstract

Context-awareness is a key ingredient in any ubiquitous and pervasive system and provides intelligence to the system, allowing computing devices to make appropriate and timely decisions on behalf of users. Context-awareness in mobile computing refers to internal and external adaptation of the environment and applications to the context state of each other. Such systems should adapt to the changes and variations of user’s context such as location, device status, connectivity and etc. In this paper we present our perspective of a context-aware service platform which is based on the idea of utilizing network information as services that is delivered via application programming interfaces and propose a fuzzy MADM method and a context similarity measure. We take into account the quality of contextual information in aggregating contextual information from different sources.

Keywords: Context awareness, Context similarity, Fuzzy MADM, pervasive computing, Service Platform, Quality of Information.

1. Introduction

Context-aware computing in mobile environment is interesting in that it paves the way for services and applications to take advantage of user’s contextual information such as time, location, and other activities. This work involves developing a service delivery framework for delivering services to mobile users where the services and contextual information are provided and collected from heterogeneous sources. Available services advertise different set of features and requirements, while available contextual information from the state of a user is limited and may not all be relevant to the decision of the best service selection. Based on the source of collected context information, the provided information is fuzzy and may not be accurate.

Quality of Experience (QoE) [1] is related to the expectations and experience of users on the performance of interactive applications and services. The concept of QoE has also been researched in the area of human-computer interaction. It is important to consider the QoE based on the actual usage and context of users. This concept also relates to the interaction of users with services or machines to services and hence it is important to make this distinction. It can be closely related to the QoS parameters. Authors in [2] argue that there is an exponential relationship between the QoE and QoS parameters with the IQX hypothesis (exponential interdependency of quality of experience and quality of service). It is often necessary to evaluate the services based on the perceived QoE seen by the end users while the QoS parameters can also play a major role.
The purpose of the future service delivery is to route the users’ requests towards the best match of their queries based on the type of requested service, requested content, context of users, and network context (connectivity). It also aims at a context-aware information exchange and QoS monitoring to enhance the usability of services and applications.

Most of the works in the area of context-aware service delivery is focused on the location as the main context. Dynamics of environment and variation of user’s context for the mobility of users has not been addressed in the previous works. While in this paper we address these issues, our proposed method is different from the previously proposed methods in the literature in that it addresses the problem of heterogeneity of context information that are collected from various sources and domains. This is done by proposing a method for the aggregation module functionality based on fuzzy measure of attributes and mapping of quality of context attributes to the required measures by our method. As mentioned earlier, QoE can also be taken into account. In this paper our perspective of a service delivery framework is also presented that is based on the context similarity measure to solve the problem of service delivery to mobile users based on the available profile and context of the user and network.

This paper is organized as follows. Section 2 provides a summary of the related work. In Section 3 context modelling and formulation in terms of quality of perceived context is discussed. Our proposed Multi Attribute Decision Making (MADM) method is presented in Section 4. Section 5 shows numerical evaluation of the proposed method. Finally, Section 6 concludes the paper.

2. Related Work

Service delivery and recommendation is widely studied in the literature. A context-aware model is proposed in [3] that proposes a context structure to recognize the changes in the dynamics of a user’s environment. In this approach the context information is categorized into static and dynamic contexts. However, it does not take into account the user’s preferences and the fact that users may access their services via a multi-modal device. The preference of users are only counted based on the previous history of service usage.

There are adaptive selection and recommendation techniques for mobile users. One of the works in this area is ACCESS [4] in which context is considered an aggregation of the user’s location, their previous history of activities and their preferences. An extension of ACCESS is proposed in [5] in which an intelligent multi-agent system for context-aware service delivery and recommendations to mobile users is presented. Another work [6] uses context to enhance the service continuity in wireless networks by proposing a middleware solution, called Mobile agent-based Ubiquitous multimedia Middleware (MUM), that performs effective and context-aware handoff management to transparently avoid service interruptions during handoffs. A prediction based approach is used in [7] where a context aware model for the delivery of content in mobile networks is presented. The proposed model in [7] learns from consumption of content on smart terminals to predict knowledge of mobile user behaviour. Relevant studies are done in the area of recommender systems [8]. The authors in [8] argue that relevant contextual information are important in recommender systems and discuss how context can be modelled in recommender systems.

Other approaches are based on context prediction. Authors in [9] have proposed a context prediction architecture and discussed some prediction methods. Another work [10] has considered context prediction by alignment method that is suitable for cases where fluctuations of user’s context is slight. In general, one of the problems with the prediction based methods is that prediction of highly fluctuating variable is computationally expensive and may require more memory resources. Another work [11] elaborates a solution on top of the existing SDPs for efficient, semantic service discovery that is context-aware and QoS-aware.

3. Representation and Modelling of Contextual Information

With the complexity of context-aware applications and heterogeneity of contextual data with different quality of information, it is important that context-aware applications are supported by appropriate model and reasoning of context [12].

Context reasoning also involves a trade-off between complexity of reasoning and expressiveness, and description logic have emerged among other logic based representation [12][13]. Some of the benefits of ontologies are capability to automatically infer new knowledge about the current context, and detect possible inconsistencies in the context data
Ontology based models of context information are widely used in various application domains. Ontologies are descriptions of concepts and their relationships. SOUPA is one of the proposals for modelling context in pervasive environments [14].

Inference of situation can be performed based on the user specified information or by automatic learning and recognition by means of machine learning techniques. The learning based approach however requires a certain training period. Examples of the learning based approaches can be found in [15, 16, 17, 18]

**Definition** Context (C) is the user related information that is used to describe the state of a user, entity or system in a specific situation [19]. An entity can be a person, location, or any object relevant to a user and/or the application. Authors in [19], have defined context as an n dimension vector in the form of:

\[ C_i = (a_1^i, a_2^i, ..., a_N^i) \]

where context attribute \( a_i^j \) is the \( i^{th} \) attribute of a context state at time \( t \). According to [20] context-aware services and applications should have the following key features. Delivering content and relevant information and services to a user, automatic execution of a service on behalf of a user and tagging of context to information to support later retrieval. Authors in [20] define a context-aware system as a system that uses context that is based on user’s tasks to provide relevant information and/or services to the user.

In inferring a situation or state, there are contextual information (attributes) that are essential and there are contextual information that are optional.

**Definition** Essential attributes are those that may have a negative influence in inferring a situation if missing or their value is not within the acceptable region of a predefined situation.

**Definition** Optional attributes are the attributes that are complimentary in inferring a situation. In other words, optional attributes can assist in a more accurate inference of a situation.

Context space \( R_i = (a_1^i, a_2^i, ..., a_N^i) \) is the domain of acceptable values that are allowed for a specific context attribute. An acceptable region \( a_i^R \) is defined as a set of elements \( V \) that satisfies a predicate \( P \) such that \( a_i^R = \{ V|P(V) \} \) [19][21]. For the purpose of this work we define the context for a user and a service / application as follows. The user’s context (aggregated context collected and formed by the assistance of access network) is \( C_i^u \) and the context of a service (describing it’s features and functionality) is \( C_i^f \). Concepts (elements of the vector) may have a different interpretation in the domain of services and the one in the users’ domain. In the domain of services and/or applications, one can interpret them as requirements or policies whereas in the domain of users they can be interpreted as preferences, features or other user related parameters. The assumption is to consider the elements of the context vectors and concepts that has a set of features \( F(C_i^u) \) and \( F(C_i^f) \) where \( F() \) maps each element of the context vector to the set of it’s features. It is assumed that \( C_i^u \) and \( C_i^f \) share at least one feature. i.e. \( C_i^u \cap C_i^f \neq \emptyset \).

### 3.1. Quality of Context and Uncertainty of Information

In developing context-aware services and provisioning of services, the availability and reliability of contextual information is of great importance. The Quality of Context (QoC) is any information related to the quality of contextual information that are involved in making context-aware decisions [22, 23, 24, 12]. Since context information can often be uncertain and incomplete in nature, it is important to provision the enforced actions based on the QoC to ensure the effective utilization of provided context information that leads to efficient context management solutions. Uncertain information can lead to uncertain reasoning and inference. Models of context uncertainty are proposed in [25] based on Gaia [26] that is a prototype pervasive computing infrastructure. Entities in Gaia can use probabilistic logic, fuzzy logic, or Bayesian networks to reason about uncertainty and author of [25] have described various ways of reasoning about uncertain contexts that are used in Gaia.

Authors in [22] and [23] have proposed a quantification approach of QoC. Furthermore, an algorithm for evaluation of QoC is also presented in [23] and the following parameters of QoC are evaluated.

1. Precision: refers to the level of accuracy. For example, a GPS receiver can locate a user with the precision of less than 10 meters, while positioning a user via a GSM cellular network may have a precision of up to 500 meters [24]. We denote the precision of collected information about attribute \( a_i \) as \( P(a_i) \).
2. Probability of correctness: refers to the probability of correctness for any given contextual information. For the previously mentioned example, there is no guarantee that the precision is true since it may depend on various other factors such as the density of the base stations in a specific area. Let $PrC(a_i)$ denote the probability of correctness about attribute $a_i$. An example of this can be collected information about the weather condition in a city. If the collected information is originated from a mobile device, it may not be correct since the mobile device can be located indoor at that time.

3. Completeness: is a representation of the degree of support that a set of attributes provide for inferring a context. Let $C(a_i)$ denote the completeness of attribute $i$, then it can be represented by the proportion of the weights of all features that support a predicate with respect to all the features.

4. Trust-worthiness: is an indication of the likeliness that the provided information is correct. It is analogous to the notion of rating in the context of sellers and customers. Let $T(a_i)$ denote the trustworthiness of the $i^{th}$ attribute and it can be measured in terms of the accuracy of the information, the previous history of collected data and statistical estimation techniques.

5. Resolution: refers to the granularity of the provided information and can be denoted by $R(a_i)$.

6. Up to datedness and time validity of information: refers to the age of the collected and provided information. For many applications, the events are time stamped and the age of the provided data play a major role. Denoting $U(a_i)$ as the time validity of a context information, it is represented in terms of the difference of the current time and most recent measurement time.

QoC can be communicated among the network entities either as metadata or separately. Our assumption in this paper is based on metadata method of communication where the QoC for each sensed data is transmitted with the data.

For the purpose of this paper we define a measure of saliency for a context information. It is an indication of the containment of attributes for inferring a predicate and the truth value of that predicate is based on the QoC parameters. The truth value function for a set of attributes on a predicate returns a truth value $\in [0, 1]$ (i.e. $\mu : R^m \rightarrow [0, 1]$).

For $m$ dimensions such as precision, trust-worthiness, completeness, timeliness, etc. The truth value of a predicate or a context information $a$ is $\mu(a)$ and it is a function of the aforementioned QoC parameters. i.e.

$$\mu_i(a) = F(P(a_i), PrC(a_i), C(a_i), T(a_i), R(a_i), U(a_i))$$

where $i = 1, 2, ..., N$ and $\mu_i(a)$ represents the truth value of context attribute $a$ collected from source $i$.

3.2. Context Aggregation

The purpose of this submodule is to collect the context information from various context providers and sources such as network context, user context, and device context information. The network context information can be obtained from the access network infrastructure via network Application Programming Interfaces (APIs) that can provide this service based on a subscription or pay per use. User context information can be obtained via transmitted query or user’s preferences or via third party applications or services where the user has shared a profile such as instant messaging, social networks and etc. The connected device capabilities can also be obtained via the third party applications and services or the access network.

Features that are required for the purpose of service selection can be inferred from different context providers with different precisions and qualities. In order to for the aggregator module to determine the context information with the required characteristics, we consider a function that returns the truth value of a predicate based on the QoC parameters for a set of attributes on a predicate and returns a truth value $\in [0, 1]$.

$$\mu : R^m \rightarrow [0, 1]$$

The truth value of a predicate or a context information $A$, $\mu(A)$ is:

$$\mu(A) = \max \{\mu_i(A)\} \quad i = 1, 2, ..., N$$

where $\mu_i(A)$ represents the truth value of context $A$ collected from source $i$. 
4. Fuzzy MADM Algorithm for Service Selection

The proposed method in this paper is based on a fuzzy MADM method called Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). TOPSIS is one of the widely used techniques for solving the MADM problems and has been successfully implemented in other various decision making problems. We modify the TOPSIS method by defining a notion of distance for context similarity measure. Traditional TOPSIS methods that have been used previously, assume all the values as crisp numbers and decision making approaches were based on a utility function of crisp valued variables defined by the decision maker. For the purpose of this work, the attributes in the MADM are not necessarily crisp numbers. Attributes can be a mixture of crisp numbers, and fuzzy numbers. Therefore, when fuzzy attributes are incorporated in a MADM problem, the preference value is no longer a crisp value. The result of the utility function is a fuzzy number with different membership functions in that interval. Therefore, ranking of fuzzy preference values would be a challenge that can be solved within the context of that given problem.

In the following we briefly explain the basic operations of fuzzy numbers for the purpose of the fuzzy MADM approach that we intend to use. We assume that fuzzy triangular values are used [27].

**Definition** Let \( \tilde{a}_i \) be a fuzzy triangular number defined as follows:

\[
\tilde{a}_i = (a_l^i, a_m^i, a_u^i)
\]

where \( l \leq m \leq u \) and \( l \) and \( u \) are lower and upper values respectively.

The procedure for the fuzzy TOPSIS MADM approach is as follows [28][27]:

1. Calculate the normalized decision matrix where each normalized value \( \tilde{r}_{ij} \) is calculated as follows:

\[
\tilde{r}_{ij} = \frac{\tilde{a}_{ij}}{\sqrt{\sum \tilde{a}^2_{ij}}} \quad i = 1, 2, ..., m \text{ and } j = 1, 2, ..., n
\]

   where \( \tilde{r}_{ij} = (r^l_{ij}, r^m_{ij}, r^u_{ij}) \).

2. Calculate the weighted normalized decision matrix

\[
\tilde{v}_{ij} = \tilde{w}_j \tilde{r}_{ij}
\]

3. Finding the ideal and negative ideal (best and worst) solutions based on benefit and cost criteria:

\[
A^* = (\max_i \tilde{v}_{ij} | j \in J), (\min_i \tilde{v}_{ij} | j \in J^c) | i = 1, 2, ..., m
\]

\[
A^- = (\min_i \tilde{v}_{ij} | j \in J), (\max_i \tilde{v}_{ij} | j \in J^c) | i = 1, 2, ..., m
\]

4. Find the Euclidean separation of each alternative from the best and worst solution:

\[
S^*_i = \sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - \tilde{v}^*_j)^2} \quad i = 1, 2, ..., m
\]

and

\[
S^-_i = \sqrt{\sum_{j=1}^{n} (\tilde{v}_{ij} - \tilde{v}^-_j)^2} \quad i = 1, 2, ..., m
\]

5. Calculate the relative closeness to the ideal solution as follows:

\[
c^*_i = \frac{S^-_i}{S^-_i + S^*_i} \quad 0 < c^*_i < 1 \quad i = 1, 2, ..., m
\]

6. Rank according to the preference order.
4.1. Ranking of Fuzzy Preferences

As mentioned earlier, the issue of dealing with fuzzy attributes raises the problem of ranking the fuzzy preferences. Ordering fuzzy numbers does not always yield to a totally ordered set as crisp numbers do. Detailed explanation of ranking fuzzy alternatives is given in [28]. Our preferred approach of ranking is based on the $\alpha$–cut approach. An $\alpha$–level set of fuzzy set $M$ is defined as follows [28]:

$$M_\alpha = \{ x \in U \mid \mu_M(x) \geq \alpha \}$$

4.2. Measure of Context Similarity in TOPSIS

In this section we describe the context similarity measurement approach to be incorporated in TOPSIS. We represent the weighted context similarity $Sim(C_i, C_j)$ between a user and a service / application as follows:

$$Sim(C_i, C_j) = \eta \left[ \sum_{k=1}^{N} w_k (a_i - a_j)^2 \right]^{\frac{1}{2}}$$

where $\eta$ is a feature similarity coefficient that is explained below and $w_k$ is the assigned weight for each attribute value. The above expression is a weighted Euclidean distance to control the effect of individual components in attribute vector onto the overall distance. The weight is determined by $w_k$ to determine the relevance of $k^{th}$ attribute. We assume that weight (influence) of each concept is between 0 and 1 i.e. $0 \leq w \leq 1$ and

$$\sum_{a_i \in C} w_{a_i} = 1$$

$\eta$ is a coefficient that helps in a pre-selection of candidate services and is based on common features. We make use of the feature similarity and feature contrast model of Tverskky [29] which indicates that two concepts are more similar when they have more common features and less non-common features. We therefore define the feature similarity of two concepts as below:

$$\eta = \frac{|F(c_i) \cap F(c_j)| - \alpha|F(c_i)\Delta F(c_j)|}{|F(c_i)\Delta F(c_j)|}$$

where $\alpha$ is a constant that is an indication of penalizing alternatives with more distinct features.

The above measure penalizes the ratio in the situation that there are not many common features. The success of the above similarity measure will depend on the degree to which the features of concepts are specified in the concepts. The above mentioned procedure can be generalized as an approach whereby the aggregated context of a mobile is formed by the collected information from the device and conditions of the access network and then compared based on the feature similarity with the advertised services on the service registry.

5. Numerical Example

In this section we provide numerical examples for the proposed method. Five attributes are considered as shown in Table 1. The service attributes are prioritized based on their importance for the objective of improving QoE for DSL services such as VOIP and IPTV [30].

| Service Attributes     | Priority |
|------------------------|----------|
| Bandwidth              | 17.2%    |
| Bandwidth variations   | 11.9%    |
| Connection Availability| 28.5%    |
| Connection Stability   | 28.2%    |
| Error rate             | 14.2%    |

Table 1: Prioritization of service attributes to improve QoE for DSL services [30].
As shown in Table 1, connection availability and connection stability together contribute 56.7% on the QoE. Bandwidth related attributes are the next major contributors.

We have used the above mentioned weight distribution approach along with the proposed MADM method to evaluate five service alternatives that demand high bandwidth. Figure 1 shows the result of fuzzy ranking preference values. As it can be shown in the figure alternative 2 is a preferred one for a high bandwidth demanding service.

6. Summary and Conclusion

Context-aware computing in mobile environment is interesting in that it paves the way for services and applications to take advantage of user contextual information. In this paper we have presented a methodology for service selection based on the heterogeneous context information, taking into account the QoC parameters. The proposed methodology can be built into a service delivery platform middleware to facilitate the provisioning of services. Attributes can be a mixture of crisp numbers, and fuzzy numbers. Therefore, when fuzzy attributes are incorporated in a MADM problem, the preference value is no longer a crisp value. The result of the utility function is a fuzzy number with different membership functions in that interval. Therefore, it is important to use the appropriate fuzzy ranking method in ranking of fuzzy preference values. Our modified TOPSIS method uses a context similarity measure that based on the feature contrast model that penalizes the distance measures with more distinct features.

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