An Approximation Approach to Discovering Web Services for Uncertain Client's QoS Preference

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Abstract. It is paramount to provide seamless and ubiquitous access to rich contents available online to interested users via a wide range of devices with varied characteristics. However, mobile devices accessing these rich contents are constrained by different capabilities e.g., display size, thus resulting poor browsing experiences e.g., unorganized layout. Recently, a service-oriented content adaptation (SOCA) scheme has emerged to address this content-device mismatch problem. In this scheme, content adaptation functions are provided as services by multiple providers. This elevates service discovery as an important problem. A QoS-based service discovery approach has been proposed and widely used to matchmaking the client QoS preference with the service advertised QoS. Most of these solutions assume that the client's QoS is known apriori. However, these approaches suffer from unknown or partially specified client QoS. In this paper, we propose an approximation approach to deal with QoS uncertainty. Our solution considers the statistical approach to discover the suitable content adaptation services. The performance analysis verifies that our approach performs reasonably well.

Introduction

There is a substantial trend in the way people communicate through the World Wide Web (WWW); browsing, uploading, downloading or storing contents. This trend is aligned with the growing number of digital contents available on the Internet. Most of the existing online contents are originally designed for display on desktop computers [1].

On top of that, the client devices vary in term of their sizes and capabilities (e.g., processing power, input and output facilities). Thus, it is becoming increasingly difficult for direct content delivery to varying devices without layout adjustment or adaptation [2]. One way to address this problem is to use devices that are capable of handling these contents. However, changing client devices to suit the content is impractical. Another solution is to adapt these contents tailored to the existing client devices. This requires a mechanism called content adaptation.

Currently, theSOCA scheme has recently emerged as an efficient paradigm to perform content adaptation on the fly [3].A complete content adaptation may require a set of adaptation tasks (e.g., summarizing full text into a short summary and translating the short Spanish summary into English audio) to a set of content objects, e.g., text and audio [4]. Each task is performed by a particular content adaptation function that potentially be provided by multiple services located across the wide-area network. Many current solutions rely on the services' QoS to match the client's QoS preference; assuming that these QoS are known apriori. However, most of the clients may not be able to provide their QoS preference (i.e., the QoS and its metrics) precisely. This is due to the fact that in pragmatic situation, a client has no idea in determining his or her QoS constraints. Our approach is motivated by the fact that the discovery system should be able to autonomously provide client with the best possible services.

In this paper, the primary practical contribution is an approach endeavors to provide the clients with appropriate content adaptation services based on QoS eventhough the client QoS is unknown apriori. The innovative aspect of our work is that the incorporation of statistical approach to discovers appropriate adaptation services. The performance of the proposed approach is studied in terms of recall during the service discovery execution under various QoS settings. The results indicate that the proposed policy performs reasonably well.

The rest of the paper is organized as follows. In Section 2, the service discovery problem is formulated. Section 3 presents the proposed service discovery framework. The performance evaluation and discussion of the results are presented in Section 4. Finally, we concluded the paper in Section 5.

Service Discovery Problem

The QoS-based service discovery problem of interest can be formulated as follow:

> Let $S = \{s_1, s_2, \dots, s_n\}$ be a set of adaptation services and $T = \{t_1, t_2, \dots, t_n\}$be a series of adaptation tasks. A service s_n is registered in a registry $R = \{r_1, r_2, \dots, r_n\}$. Each task t_n can be performed by multiple adaptation services and will be selected based on quality of service (QoS) criteria$Q = \{q_1, q_2, \dots, q_n\}$. Example of QoS criteria are time (e.g., response, transport and adaptation), cost, availability and rating. In this paper, we assume that the client does not set any predetermined bounds (e'g', maximum and minimum values).

Given a set of *S*, *R*, *T* and *Q*, the central problem is how to discover a set of appropriate services correspond to a series of adaptation tasks with the aim of providing the best (if possible) QoS offers. Graphical representation of the aforementioned problem is shown in Figure1.

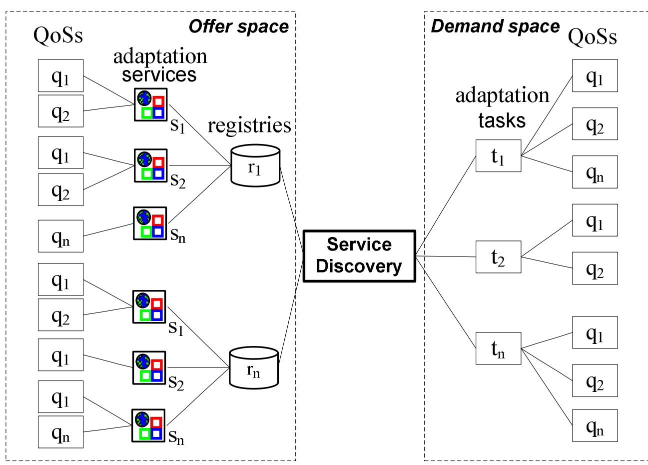


Figure 1:Service discovery scenario

Service Discovery Framework

The service discovery framework (Figure 2(a)) consists of essential components that provide access to obtain the services descriptions including the QoS; fetch client QoS preference (i.e., in term of attributes, but not the specific maximum or minimum QoS attributes' values); tabulate services using statistical approachincluding refining solution space λ*;and provide the result**λ**. In the service listing scheme, the business registries publish the available adaptation services and they are distributed across the Internet. We adopted service crawler engine presented in [5]. The client states their QoS attributes preference through service level agreement (SLA) handled by the broker [6]. The discovery system acquires the service parameters (i.e., functional (e.g., operation's name and input output), and non-functional (e.g., QoS descriptions and its parameters) and the client preference (e.g., operation required, QoS parameters)). Service descriptions construct the offer space while the client preference constructs the demand space. Mapping these two spaces create the solution space (i.e., discovery list). The refinement function is responsible for providing reasonable and minimized solution space (i.e., recall and length).

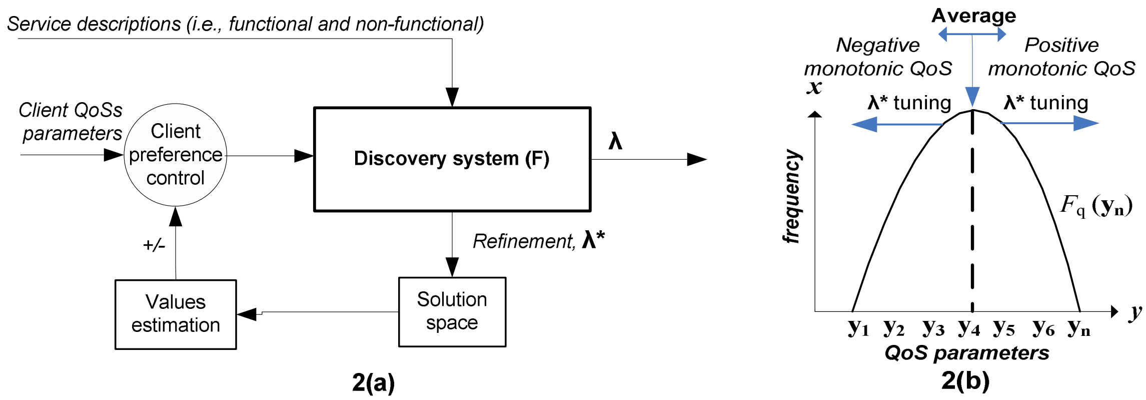


Figure 2(a):Service discovery framework; 2(b) Normal skew distribution with targeted area for positive and negative monotonic QoS

Building Solution Space using Statistical Approach

For any adaptation service, the considered parameter for any QoS has the form of cumulative distribution function $F_q^S(X)$ as follow:

$$F_q^S(X) = P\left(\delta_q \le X\right) \text{where} \forall X \in \mathbf{R}_+. \qquad (1)$$

where δ_q is the random QoS parameter and ranges over domain of this QoS parameter. $\mathbf{R}_+$ is any real number within the observed QoS domain. $\mathbf{R}_+$is the measured QoS parameters within a considered QoS and can be fitted in a particular distribution function $F_q(Y)$.

$F_q(Y)$ can be abstracted by (1) a finite set of percentiles (e.g., the set of values $y_1,\ldots..y_k$ such that $F_q(y1) = 10\%, \ldots, F_q(y9) = 90\%$), or (2) location (e.g., the set of values $y_1,\ldots..y_k$ such that $F_q(y1) = a, \ldots, F_q(y9) = i$), or (3) statistical pattern (e.g., the set of values $y_1,\ldots..y_k$ such that $F_q(y1) = a, \ldots, F_q(y9) = i$). Such ranges are easily expressible in terms of WSLA standard[7].

As depicted in Figure 2(b), to get the desired solution space size (i.e., discovery result λ), we can tune the Y for $F_q(Y)$. For positive monotonic QoS, a soft *super* offer is obtained by sliding Y to the right side of the x-axes. This will eventually result in a smaller solution space. For negative monotonic QoS, a soft *super* offer is obtained by sliding Y to the left side of the x-axes. An average (including mod and median) position can be obtained by using a typical average function in statistical domain. The service s_n with the QoS q_i parameter δ_{qi} will be listed into λ if it satisfies the following:

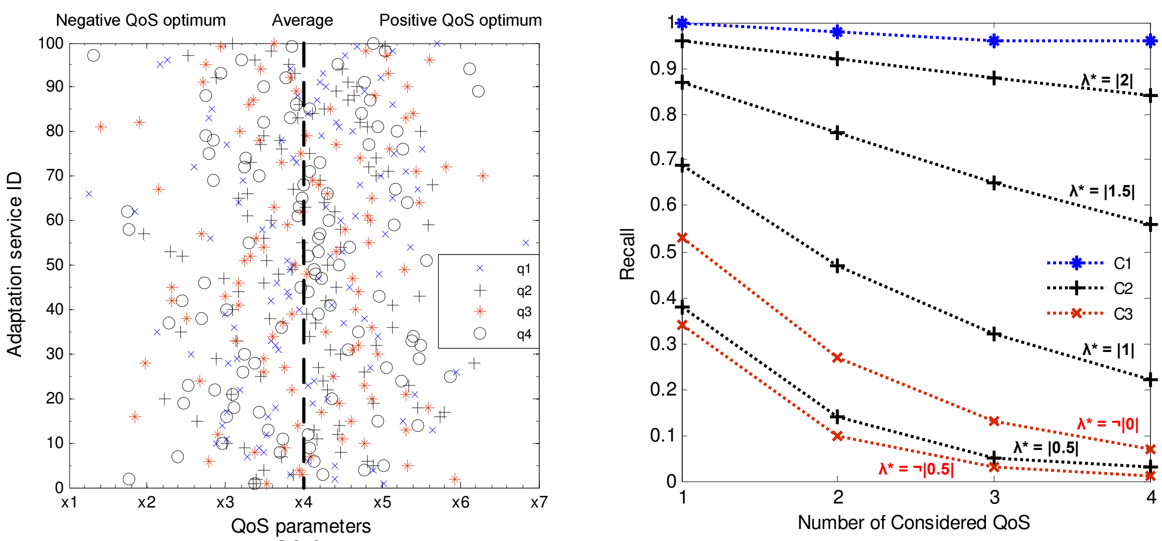
$$\forall q, q = \{1, \ldots, N\}, \delta_q.q \cap F_q\left(y_q\right) \neq \emptyset .(2)$$

Equation (2) indicates that if q for the service s_n is within the desired ranges, the service s_n shall be listed into the final list λ.

Performance Evaluation, Results and Discussion

We use experiment to study the efficiency of the proposed service in term of recall length. Having a recall with high precision improves the service discovery execution. We followed the verification methodology descibed in [8]. To perform the experiment, data to represent the QoS' values is generated based on skew distribution as the skew distribution is often useful to fit observed data with "normal-like" shape of the empirical distribution but with lack of symmetry [9]. The observation in [10] regarding 20,000 measured delay time for *USWeather* Web service depicted that the measured data can be fitted into positive skew distribution. The data sets are generated from the skew distribution data generator provided by [9].

Figure3(a) illustrates the generated mixed integer for QoS parameters of 100 adaptation services using skew-normal distribution. In the experiment, we varied the number of QoS from 1 to 4 (consisting of two positive monotonic and two negative monotonic). As can be seen from Figure3 (a), the distribution of the generated QoS parameters can be statically grouped into three different locations: middle, left and right along the x-axis. The left side of the x-axis represents the optimum parameters for negative monotonic QoS while the right of the x-axis represents the optimum parameters for positive monotonic QoS. We can simply replace the x1 to x7 ranges with percentile or numerical values [7]. In our case, we replace the x1 to x7 ranges into numerical real integer between -3 to 3 (i.e., |3.0|).



3(a) **3(b)**

Figure 3(a) Randomized Mixed Integer QoS Parameters for 100 Adaptation Services; 3(b) Recall Comparison

Then, one experiment was conducted to study the service discovery execution towards recall. Recall is the number of relevant returned adaptation services to the query {correct}, with regard to total relevant adaptation services in the corpus $\Re_L$ (i.e., the total relevant services that should have been returned). In our case, $\Re_L$is the total of adaptation services in the same group.

$$Recall\ (\lambda) = \frac{|\{correct \in returned\} \cap \{returned \in \Re_L\}|}{|\{\Re_L\}|}. (3)$$

In term of experiment variation, C1 defines that all services that contain QoS metrics specified have the same priority and to be considered equally during discovery. C2 represents that in order for a service to be discovered from list L, all the associated QoS metrics must be within average ranges (i.e., λ^*) approximate by the system. C3 is the combination of QoS that have the parameters in the maximum distribution location ranges (i.e., to the right of x-axes for positive monotonic QoS and to the left of x-axes for the negative monotonic QoS).

Figure3(b) shows the reduction ration (y axis) as a function of the QoS (x-axis). In this experiment, we varied the λ^* for C2 (i.e., within |0.5|, |1.0|, |1.5| and |2.0|) and C3 (i.e., ¬|0| and ¬|0.5|). The number of QoS is between 1 to 4 and increases by one for each step. As can be seen from Figure 3(b), C1 generated the highest recall for QoS variations compared to the others. The recall decreases along x-axis for all conditions and its variations. C1 constantly produces recall ≈ 1 while C3 produces the least recall. This implies that by non-prioritize the considered QoS will result in bigger recall. There is a considerable different of the recall between C2 variations with λ^* =|2.0| provides the highest, while λ^* =|0.5| provides the least. A (1) 10% margin is observed between C2 λ^*

=|2.0| and λ^* =|1.5|, and increased by 10% for each step, (2) 20% margin is observed between C2 λ^* =|1.5| and λ^* =|1|, and increased by an average 20% for each step, and (3) 30% margin is observed between C2 λ^* =|1| and λ^* =|0.5|, and remains steady for each step. This indicates that by applying smaller λ^* value for C2 will result in smaller recall. C3 provides the least recall compared to others. There is significant reduction within C3 variations which in average is around 20% for each step along x-axis. A 10% margin is observed within C3 for λ^* = ¬|0| and λ^* = ¬|0.5| for each step. This indicates that a lower negate λ^* value will result in higher recall. In this experiment, the recall decreases along x-axis for all conditions C1, C2 and C3. We also found that the recall is less when is λ^* value is (1) smaller (≤ |0.5|) for C2, or (2) bigger (≥ ¬|0.5|).

Conclusion

The increasing diversity and heterogeneity of devices, data sources and networks pose a challenge in the delivery and consumption of multimedia content. In this paper, we proposed a service discovery framework for SOCA. In summary, the proposed framework was able to clearly meet its objective and can be used to bridge between current semantic discovery [11] and QoS-based discovery systems. The solution using statistical approach has been simulated. The experiments results showed that the solution can provide the client with reasonable solution space. The proposed framework can be easily incorporated with any QoS-based service selection mechanism. As our current system is beneficiary to the client, we also are working on to extend the discovery system that also will be beneficiary to the content adaptation service providers by providing feedback on the current observation of QoS metrics and client preference [12]. Also, we want to anticipate the user's device energy status as one of the SLA consideration [13].

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