A Dynamic Planning Framework for QoS-Based Mobile Service Composition Under Cloud-Edge Hybrid Environments

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Abstract. In cloud-edge hybrid environments, when QoS constraints of the SOA-based mobile service composition change, a dynamic reconfiguration needs to be performed. Different from the traditional cloud service, the cloud-edge hybrid environment has the characteristics of limited resource storage, limited energy at the edge and uncertain users who move frequently. Dynamic reconfiguration in this mode is challenging. QoS is an important indicator of service evaluation. Most studies focus on only the static QoS attributes of the service. However, the QoS of a service is not statically constant; it changes dynamically over time. Therefore, to avoid the immediate failure of the service and ensure the stability of the mobile service composition after dynamic reconfiguration, an LSTM neural network is applied to predict the future QoS value for candidate service. This value is used as a service evaluation indicator during dynamic reconfiguration. Then, attributes such as energy consumption, traffic and moving track are considered. A cost-reward mechanism is constructed to calculate the cost and reward of the service when it is invoked. The reasonable restriction conditions are added for controlling dynamic reconfiguration. Finally, the dynamic reconfiguration problem-solving process and framework for mobile service composition based on QoS in a cloud-edge hybrid environment is introduced, guiding the mobile service composition dynamic reconfiguration task in cloud-edge hybrid environments.

Keywords: Cloud-edge hybrid environments · Mobile service composition · Service QoS · Service failure · Dynamic reconfiguration

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1 Introduction

With the rapid development of mobile devices and cloud computing, cloud-edge hybrid environments have been widely known for its powerful computing capacity [1]. In this model, users can invoke services provided in the cloud or deployed on edge devices to achieve high-performance, low-latency, and high-bandwidth service interaction experiences [2]. However, due to the heterogeneity, openness and synergy of the network in cloud-edge hybrid environments, the reliability and correctness of service-oriented applications are seriously affected [3]. For example, as the geographic location of a mobile device changes dynamically, there will be unpredictable latency in the communication process, resulting in application failure behavior. Therefore, it is necessary to propose a dynamic reconfiguration scheme for the application of mobile service composition in cloud-edge hybrid environments [4].

QoS is an essential indicator for evaluating services in dynamic reconfiguration [15]. If quality of service (QoS) constraints need to be improved, the dynamic reconfiguration process [16] can be completed by replacing the service with a higher QoS value in the application. The existing research mainly focuses on the dynamic reconfiguration problem of the static QoS value of traditional services [5]. This method mainly has the following shortcomings: (1) Because of the instability of network environments in mobile environments, the attributes such as signal strength, response time and reliability of mobile devices are affected, and dynamic fluctuations in service QoS will occur [14]. Dynamic reconfiguration of a service based on the current QoS value will cause the application to be in an unstable and unreliable state. (2) Another unavoidable problem with cloud-edge hybrid environments is decreasing the energy consumption of mobile terminal devices [6–8]. With the exponential growth of mobile devices, an increasing number of mobile applications are attempting to accomplish more complex logic functions [9]. In addition, to improve application performance and reduce energy consumption of mobile devices, it is necessary to address the energy consumption problem [11].

To solve the above problems and ensure the stability of the application in the running process. We use a long short-term memory (LSTM) neural network to predict the dynamic QoS of the service [12, 13] and build the service value attributes as an optimization selection target. The service cost and reward attribute that guide service dynamic reconfiguration process are evaluated. Finally, the dynamic reconfiguration problem is formalized, a suitable solution is obtained, and a framework to unify the above processes is built.

The remainder of this paper is organized as follows. Section 2 presents the formal definition of cloud-edge services. Section 3 describes the quantitative calculation of service-related attributes in the dynamic reconfiguration process. Section 4 uses the LSTM prediction model to predict the QoS value of services. Section 5 integrates previous papers and builds a dynamic reconfiguration framework for mobile service composition under cloud-edge hybrid environments. Section 6 presents conclusions and provides future research directions.

2 Formal Definition

In this section, according to the characteristics of the cloud-edge hybrid environment, the definitions of cloud-edge service, service plan, service invocation and composite services are given first for clearly showing the related concepts.

2.1 Definition of Cloud-Edge Service

Definition 1 (Cloud-Edge Service): A cloud-edge service can be represented as a triple (i, o, $\{QoS_t\}$), where:

1. i is the input parameters;
2. o is the output parameters;
3. $\{QoS_t\}$ is a chronological sequence of quality of service.

The cloud-edge service can be either a traditional web service or an edge-end service deployed on a variety of sensors. The service QoS value records the quality of service sequence for a certain period. It can effectively reflect the dynamic change trend of service quality.

Definition 2 (Service Plan): A service plan can be represented as a triple (T, P, B), where:

1. $T = \{\mathrm{t}_i\}_{i=1}^{n}$ is a set of tasks, including two mutually disjoint subsets FT and CT, where FT is the functional task subset, and CT is the control task subset;
2. P is a set of settings in the service plan (e.g., execution probabilities of the branches and loops structures);
3. B provides the structural information of the service plan, which can be specified by XML-based languages such as the business process execution language (BPEL).

The service plan is an abstract description of the business process. There are two types of tasks in a service plan: functional tasks to imply functional requirements, and control tasks to flow directions. The control tasks can coordinate and monitor the structure of the service and ensure the relationship between functional tasks. Given the two tasks, t1 and t2, the four compositional structures are shown in Fig. 1. The structure of the service plan is divided into four categories: sequence, choice, parallel, and iteration. In different structures, each service attribute is calculated differently.

Definition 3 (Cloud-Edge Service Invocation): A cloud-edge service invocation can be represented as a tetrad (t, s, $cost$, $reward$), where:

1. t indicates the tasks performed in the service plan;
2. s is the service invoked to realize t;
3. $cost$ is the cost during the invocation of s;
4. $reward$ is the cost during the invocation of s.

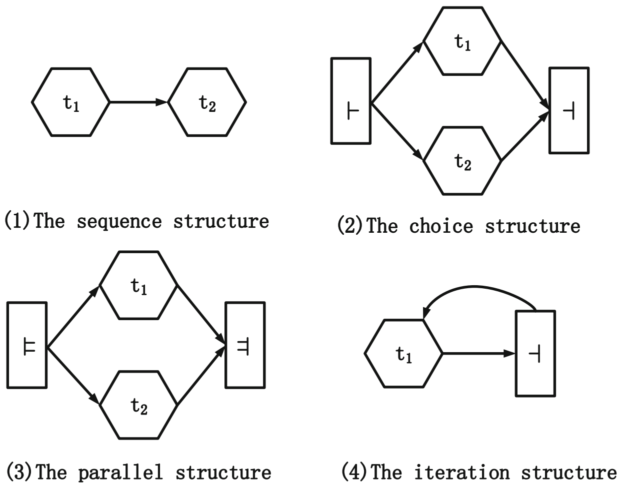

Fig. 1. Compositional structures.

In a cloud-edge hybrid environment, the service plan is implemented by a set of service invocations, each corresponding to a service invocation and an appropriate service. In the process of calling a cloud-edge service, a certain number of costs and rewards will be generated. For example, the energy consumption and traffic expense of calling a service are service costs. However, while data redundancy requires a large budget, more data can improve data quality to some extent [18]. So, we define the strength of the service collection data as a reward for calling the service.

In addition, the cost and reward calculations for composition services are not the same for different workflow structures in the service plan [15]. Given a structure S consisting of S1, S2, …, Sn, and n subservices, we give the calculation of cost and reward properties under four service portfolio structures.

1. Sequence

$$\cos t_s = \sum_{i=1}^{n} \cos t_{si},\ reward_s = \sum_{i=1}^{n} reward_{si}$$

2. Choice

   Assume the probability of selecting the first branch in the selection structure is P_i, and $\sum_{i=1}^{n} p_i = 1$.

$$\cos t_s = \sum_{i=1}^{n} \cos t_{si} p_i,\ reward_s = \sum_{i=1}^{n} reward_{si} p_i$$

3. Parallel
   In a parallel structure, the entire application does not continue until all branches have completed the operation. The service cost and reward attribute calculations in a parallel structure are essentially the same as the sequential structure, as follows:

$$\cos t_s = \sum_{i=1}^{n} \cos t_{si},\ reward_s = \sum_{i=1}^{n} reward_{si}$$

4. Iteration
   Assume that the loop body is executed m times. Service invocation costs, such as energy and traffic, will also increase m times. On the other hand, the reward for calling the service is defined as the strength of the service collection data. In this case, the service is executed m times, but the data collected by the service is the same each time. Therefore, the reward will not change in this case. The service cost and reward are as follows:

$$\cos t_s = m * \cos t_{si},\ reward_s = reward_{si}$$

Definition 4 (Cloud-Edge Composite Service): A cloud-edge composite service can be represented as a triple (*S*, *B*, *QoS*), where:

1. *S* is the set of web services and edge service set constituting the composite service;
2. *B* provides the structural information of the service plan;
3. *QoS* expresses the quality of the composite service.

A cloud-edge composition service is a collection of services that consist of edge services and web services. A cloud-edge composite service is implemented through a set of service invocations where the appropriate service implementation is selected for each task.

3 Quantitative Calculation for Service Properties

3.1 Service Value

The value property of the service is used as a measure of service availability in dynamic reconfiguration. In determine that the service does not expire and reduce the potential operational risk, it is necessary to accurately predict the future QoS value of it [19, 20]. Therefore, taking into account the QoS attribute value and the predicted QoS property value of the service, we assign a value property to each service, which represents the importance of the service to the application's dynamic reconfiguration. Based on the above description, we model the value function of the service $s_i \in S$ as follows:

$$\begin{aligned} value_k(Q(T_i), Q(T_{(i+1)}), Q(T_{(i+2)})) &= \frac{\int_{T_i}^{T_{(i+2)}} f(x)dx}{T_{i+2} - T_i} \\ &= \frac{\frac{T_{i+2}-T_i}{6}[Q(T_i) + Q(T_{i+1}) * Q(T_{i+2})]}{T_{i+2} - T_i} \end{aligned}$$

Among them, $value_k$ represents the value function of service k. Its value is determined by the $Q(T_i)$, $Q(T_{i+1})$ and $Q(T_{i+2})$. Where, $Q(T_i)$ is the service QoS value at the current moment, $Q(T_{i+1})$ is the QoS value at T_{i+1} moments and $Q(T_{i+2})$ is the QoS value at T_{i+2} moments. $Q(T_{i+1})$ and $Q(T_{i+2})$ are predicted using the LSTM neural network. $value_k$ is an improved service metric. It is determined not only by the current QoS of the service but also by the possible QoS values of the service in the coming period.

3.2 Cost-Reward Mechanism

The mobile service composition in the cloud-edge hybrid environments has many complex characteristics. When the dynamic reconfiguration problem of service is formalized, it is not enough to improve the QoS value of service composition. It does not guarantee the efficient and reliable operation of the application after dynamic reconfiguration. Therefore, the different characteristics and the specific factors of mobile service composition are considered to define the service cost and reward attributes. The attributes can improve the efficiency and reliability of the application after dynamic reconfiguration.

3.2.1 Service Cost

We define a cost attribute for each service. It can be divided into two parts, energy consumption cost and traffic cost. For a service $s_i \in S$, its cost is defined as:

$$c_i(E_i, D_i) = \alpha_i E_i + \beta_i D_i$$

where c_i represents the cost, E_i represents the energy consumption and D_i represents the traffic expense in the process of calling service i. α_i and β_i represent the weight of the traffic expenses and energy consumption, respectively.

First, for traffic consumption D_i, the calling environment is dynamically changing, and the user is frequently moving. However, the traffic calling the service is fixed and does not change dynamically as the service objects and the service providers may move. Therefore, the definition of D_i is as follows:

$$D_i = ud_i + dd_i$$

where ud_i is the quantity of upload data required to invoke service i, and dd_i is the quantity of download data required to invoke service i.

Second, we focus on the impact of the mobile environment on energy consumption during service invocation. The calculation of energy consumption in traditional cloud-edge hybrid environments is usually static [14]. However, due to the dynamic change in the location of the service caller, the network signal strength is unstable. It leads to fluctuations in the transfer rate when the data are uploaded and downloaded. As well as the response time changes a lot. Ultimately, the energy consumption of the device is also in the process of dynamic change. The energy consumption computation model in paper [17] is used to calculate the energy consumption E_i of service i in a mobile environment. The definition of the mobile path of the service caller is given below.

Definition 5 (Mobile Path): A mobile path is represented by a triple *(T, L, F)*, where:

1. $T = \{(t_i, t_{i+1})\}_{i=0}^{n-1}$ is a set of discrete time intervals, with as the start time and as the stop time;
2. L is a set of discrete location points;
3. F is a function representing the correspondence between time and location: $\forall t \in (t_0, t_n) F(t) \rightarrow L.$

Where function $F(t)$ represents the correspondence between time and position. Given a point in time, we can obtain the position that corresponds to the user at that point in time.

Although the signal strength in the mobile environment changes dynamically, the signal strength of the same path segment after the path is refined is usually stable and can be measured. We define the formula for the energy consumption E_i of service i in a mobile environment as follows:

$$E_i = uc + sc + dc$$

The energy consumption of uc when uploading data in the process of calling service i is calculated as follows:

$$uc = \frac{D(i)}{H(G(l_1))} \times (R(G(l_1)) + sp)$$

where $D(i)$ is the data size; $l_1 = F(t_1)$, which is the corresponding path point for the user at time t_1; $H(G(l_1))$ is the data transfer rate at location l_1 at the time of the upload. The signal strength is $G(l_1)$. Similarly, $R(G(l_1))$ is the location l_1 where the data are uploaded. The radiation power of the device when the signal strength is $G(l_1)$. The standby power for the mobile device is sp. And, sc is the standby energy consumption of the device while waiting to execute the service; the calculation method is as follows:

$$sc = sp \times rt$$

Among them, rt is the response time of the service, and the energy consumption of dc for downloading data is calculated as follows:

$$dc = \frac{D(o)}{H(G(l_2))} \times (R(G(l_1)) + sp)$$

$$l_2 = F(t_1 + \frac{D(i)}{H(G(l_1))} + rt)$$

Therefore, we use the energy consumption computation model to calculate the energy consumption of service calls in a mobile environment. Furthermore, the cost of the service is calculated. During the dynamic reconfiguration process, the cost attribute value for each candidate service represents the costs of calling the service. The higher the cost value of a service, the greater the cost of calling the service.

3.2.2 Service Reward

The cost of calling different services is different, but this does not mean that a service with a lower cost should be invoked as a priority. The relationship between the quantity of data uploaded and downloaded by the service and the QoS is subject to the marginal benefit rule to some extent [18]. In other words, when the service receives more upload and download data, to a certain extent, it will improve the accuracy of the data to ensure the quality of the service. However, as a result of the reduction in the marginal increase of the data quality, data redundancy is generated. It inevitably leads to a waste of resources. For service $s_j \in S$, D_j represents the quantity of data that the service uploads and downloads. The corresponding reward for the service is:

$$r_j(d_j) = \gamma_j \times e^{-\lambda_j d_j}$$

Among them, λ_j is the initial reward of service J, which is a parameter to control the marginal decreasing effect of the data. A larger λ_j indicates that the reward of the service decreases faster as the quantity of uploaded and downloaded data increases.

3.2.3 Formal Dynamic Reconfiguration

The value property of the service is used as a metric to evaluate whether the service is available. As described earlier, the value property of a service is an important parameter for applying the current and future QoS property values. The greater the value of the service, the greater its effect on improving the current and future QoS values. Therefore, the goal of dynamic reconfiguration is to maximize the values of the mobile service composition application.

In addition, for mobile service composition applications, the cost and reward of calling each service are different. From the user's point of view, the cost of calling services should be no higher than its value. In summary, the application of dynamic reconfiguration in mobile service composition under cloud-edge hybrid environments can be formalized in the following form:

$$\max. \sum_{k=1}^{s} value_k$$

$$s.t. \sum_{s_i \in S} c_i \leq \sum_{s_i \in S} r_i$$

Among them, the first formula indicates that the goal of dynamic reconfiguration is to maximize the value of the application. The second formula is the constraint condition of the dynamic reconfiguration problem, that is, the application cost should not be greater than the reward. Note that S is a collection of all services in the mobile services composition app.

4 LSTM Model for Predicting Service QoS

In a mobile environment, the quality of service will change as the location of the service changes dynamically. This may cause the service to fail. To ensure the stability of dynamic reconfiguration and reduce the risk in application operation, an LSTM neural network is employed to predict service QoS.

As shown in Fig. 2, this paper constructs an LSTM prediction model with an LSTM loop layer and two full-connection layers. The service response time, throughput, current signal strength and other parameters are selected to predict the service QoS value. The predictive model framework of the LSTM neural network is similar to conventional fully connected neural networks, except that some hidden layers in the network are replaced with LSTM structures. The input of the model is a sequence of attributes. It affects the change of service QoS value and the output predictive service QoS sequence in the cloud-edge hybrid environment.

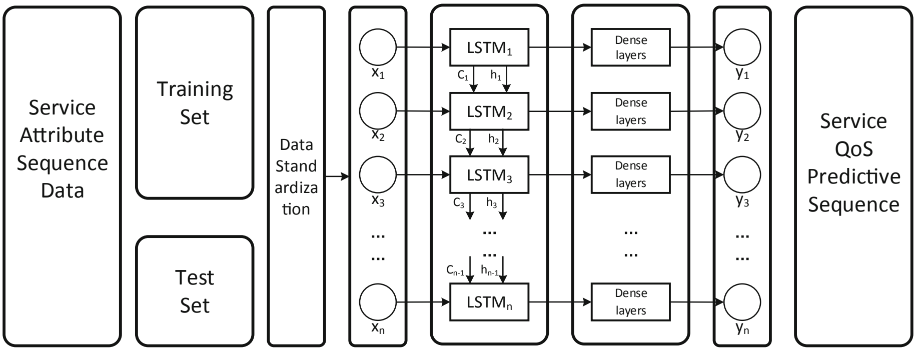

Fig. 2. LSTM neural network predictive model framework

The training process of the LSTM neural network is similar to conventional fully connected neural network. First, the feedforward propagation is used to input the training data into the network. The output value of the LSTM unit is calculated. Then the feature is extracted by two layers of the fully connected layer so that the layer is trained to the output layer. The "predictive estimate" of the sample data is obtained. Second, the error value of each neuron is calculated backward. The reverse propagation of the LSTM neural network consists of two functions. One function is the reverse propagation along time; that is, the error entry at each moment is calculated from the current T moment. The other function propagates the error item to the upper layer, according to the corresponding error item. By calculating the gradient of each weight, the model parameters are adjusted so that the prediction results are close to the optimization target. Through the above iteration, the training obtains the required optimization objectives to establish an LSTM neural network prediction model to meet the error requirements.

5 Framework

As shown in Fig. 3, the mobile service composition dynamic reconfiguration framework includes the candidate service value solving process, the service constraint condition solving process and the service dynamic reconfiguration process. The process of solving the service value is the process of calculating the importance parameters of the candidate service to the dynamic reconfiguration of the application. The process of solving the cost and reward of each service is measured by the service constraint condition. Finally, the final dynamic reconfiguration process selects the appropriate scheme in the candidate service to satisfy the new QoS constraint process.

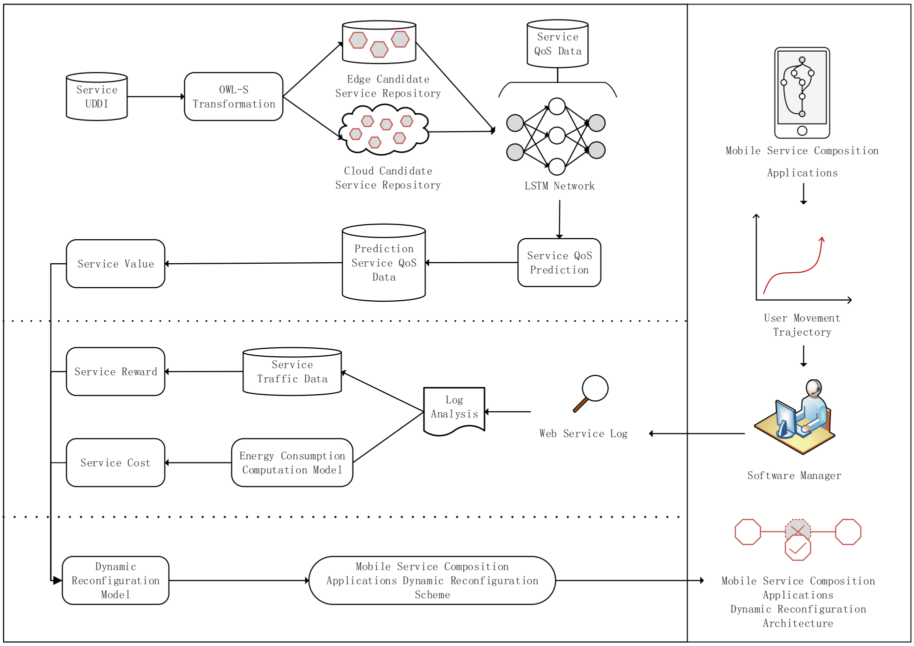

Fig. 3. Mobile service composition application dynamic reconfiguration framework

Solving the importance parameters of the candidate service for dynamic reconfiguration of the application is divided into two steps. The first step trains the LSTM neural network using the web service QoS dataset and the service invocation information collected from the sensor. The candidate service dataset from the cloud and edge end is the input variable to predict its QoS property value. The input dataset primarily contains a sequence of properties that have a greater impact on applications in cloud-edge hybrid environments, such as response time, throughput, and signal strength of the service. The second step combines the QoS property values at the current time and the predicted QoS property values for a future period of time to calculate the importance value of the service for this dynamic reconfiguration. It is based on the value function calculation formula.

In the second phase of the dynamic reconfiguration framework, we first analyze and process the log information of the candidate service. Then, the available information is extracted. We collect the mobile user's trajectory and place it into a grid to build the mobile trajectory model. The model is used to further handle changes in the signal strength of the user's device during the invocation of the service. The dynamic fluctuation of service-related property values caused by the changing environment of the user is one of the factors considered in this step. Finally, the mobile trajectory data and service upload and download, response time, signal strength and other attributes are combined. The service flow consumption, energy consumption and service reward are calculated according to the traffic calculation formula and energy consumption computation model, respectively. In this step, the factors that have a significant impact on the reconfiguration process are considered. Those factors guide the dynamic reconfiguration process.

Finally, according to the service value, service cost, service reward, and other attribute values sought in the above two stages. A formal dynamic reconfiguration model is used to solve the better scheme of dynamic reconfiguration in cloud-edge hybrid environments. The main goal of the dynamic reconfiguration model maximizes the value of the application. In the process, it is necessary to ensure that the cost of calling each service is lower than its reward so that the planned application as a returned result has the characteristics of low energy consumption, high stability, high reliability and so on.

6 Conclusion

Aiming at the related characteristics in cloud-edge hybrid environments, a dynamic reconfiguration framework for mobile service composition application is proposed. The process of this framework is divided into three stages. The first stage quantifies the service measurement standard in the cloud-edge hybrid environment and clarifies the service value solving process. The second stage summarizes the service constraint quantification process and clarifies the service cost and the return solution process. And the third stage identifies the data flow direction of the dynamic reconfiguration model. By constructing the dynamic reconfiguration framework of mobile service composition in the cloud-edge hybrid environment, the dependence of each module and the reconfiguration process are shown clearly.

In the next step, the dynamic reconfiguration framework proposed in this paper will be implemented and transformed into a real application, and the dynamic reconfiguration problem under this model will be standardized. In addition, structural optimization and loss function of the neural network will be considered to further improve its performance, such as using user collaboration and Microservice deployed in mobile App.

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