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Ant-based service selection framework for a smart home monitoring environment

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Abstract Selecting ambient media services in a smart home monitoring environment is challenging. Services in such an environment should be ubiquitous, adaptive, and robust with respect to access and delivery. Many different techniques exist for selecting services in smart environments, for example, dynamic programming, genetic algorithms, and fuzzy logic. However, existing approaches to service selection fail to address the dynamic nature of the services and the requirement of considering the user context and user satisfaction. We address this issue by proposing an ant-inspired service selection framework based on dynamic user preferences and satisfaction. This ant-inspired approach is robust to failures and adaptive to dynamic context. The proposed framework enables different categories of residents (e.g., elderly people, fathers with children, mothers, and so on) to access various media services in such a way that their experiences are optimized with regard to their surrounding environment. Experimental results demonstrate the viability of the proposed framework.

Keywords Smart environment · Ambient media service · Ant based selection · Service composition

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1 Introduction

The presence of heterogeneous technologically augmented devices, sensors, and services offers new ways of dealing seamlessly with ambient media [19] access. It is obvious that the goal of ambient media access is to enable universal media access in a smart home monitoring environment, which considers the delivery of different media under different usage environments (i.e., context). Such a goal also drives the vision of Ambient Intelligence (AmI) [1], which enables technology to be unobtrusive, embedded in our natural surroundings, and adaptive to the response of people and their dynamic context. In this domain, media services should be accessible to different kinds of users (e.g., a father with his children, a young couple, and elderly people) from anywhere at any time, and should be able to be rendered to any device over heterogeneous networks in a smart home monitoring environment.

Many available heterogeneous media services (e.g., movies, music, images, news, RSS feeds, and sports) provide similar functionality, but have varied capabilities and resources in terms of computation power, display (e.g., resolution and colors), and memory. In addition, users of these services might have different preferences, including preferences of types of media services, presentation, and accessibility. To provide flawless access to these media services, it is essential to select appropriate services to ensure that the media is acceptable to the users based on a desired level of satisfaction by considering their changing surrounding context.

Currently, there are numerous existing studies related to web service selection [3, 7], multimedia service selection [10, 30], location-aware service selection [18], and context-aware media recommendation [6, 9]. Only a few of these, however, have addressed ambient media service selection [12, 13] or ant-based media service selection [11, 14]. Due to a) the rich semantics of ambient media, b) the complexity and dynamic characteristics of smart home applications, and c) the surrounding context of the user as well as heterogeneous media itself, existing research is not directly applicable to the selection of ambient media services.

In this paper, we propose a framework that addresses the above issues by incorporating an ant-based media service selection approach, while considering the dynamic user context so that user satisfaction can be maximized. The proposed framework is evaluated through implementation and experimental results.

Our contribution in this paper is two-fold. Firstly, in order to have a dynamic ambient media service selection and composition in a smart home monitoring environment, we provide a mathematical model to calculate and update user preferences in real-time. Secondly, we introduce an ant-based selection approach to the proposed framework so that satisfactory customized service can be assured by composing heterogeneous media services based on the varied user context. This user context is crucial for smart home monitoring environments, where different categories of users (e.g., a father with his children, a young couple, and elderly people) can access customized services based on their preferences. We call this the Ambient User Media Preference (AUMP).

The remainder of this paper is organized as follows. Section 2 provides a formal problem statement followed by Section 3, which describes related works. In Section 4, we elaborate on our proposed work. Thereafter, we briefly describe implementation issues and development challenges in Section 5. We conclude our work in Section 6 together with listing possible future research directions.

2 Problem descriptions

Let us consider a typical scenario of a client requesting a particular service, which requires accessing different available services. To accomplish the desired task, users may require access to various services such as a movie service, audio/music service, news service, and so on. We describe the problem of the selection of these services in a smart home monitoring environment as follows.

- Assume that a system, consisting of ambient media services, can be composed to respond to a user's request. Let the set of services, **S** be denoted as, $\mathbf{S} = \{s_1, s_2, \ldots, s_n\}$. We also assume that, at a given time, the system identifies one user in the environment and selects services to his satisfaction.
- Let each service s_i,$1 \leq i \leq n$ be characterized by two attributes $\langle U_i, Q_i \rangle$
  - $U_i \in [0, 1]$: This denotes the satisfaction of a user in using service s_i based on the user context, which is discussed in Section 4.2. We propose an ant-based approach, which estimates the user satisfaction from selected services based on the AUMP and QoS, which is also discussed in Section 4.2.
  - The QoS constraints include delay, bandwidth, and frame rate, and are represented by $Q_i \in \{q_1, q_2, \cdots q_n\}$. However, in our particular experiment, we use only delay in the QoS constraints,$\sum_{i=1}^{n} d_i \leq D_{\max}$, where total cumulative delay ($\sum_{i=1}^{n} d_i$) for all selected services must not exceed the maximum acceptable delay ($D_{\max}$) threshold.

Our objectives in this paper are as follows:

- to describe an ant-based service selection framework in a smart home monitoring environment; and
- to ensure that, in this environment, services are selected in such a way that maximizes overall user satisfaction (U_i) subject to the QoS constraints, $\sum_{i=1}^{n} d_i \leq D_{\max}$.

3 Related work

The proposed research addresses media service selection based on user preference, QoS, and the surrounding context using an ant-based selection approach. So, the proposed work is related to a variety of interrelated interdisciplinary research efforts such as context-aware media service selection, ant-based service selection, QoS-aware AmI service provision in smart homes, and so on. Here, we attempt to describe some of these.

Context-aware media service selection is not new in a personalized user ambient environment. Researchers have attempted to identify a suitable approach for context- aware media recommendation. A notable work is [23], in which the authors state that context-aware media recommendations consist of three types:

time-based, mood-based, and social recommendation. Considering all of the three types in a dynamic real-time context is very difficult due to the varying parameters. In their work, they used two real world anonymized datasets containing contextual information like mood, social network, and comments that are not normally available in a movie database. Other works related to context aware movie recommendations are [6, 9].

A location-aware service selection mechanism is presented in [18]. In this approach, the geographical area of a target environment is divided among several service domains, where a set of services is restricted to a service domain, such as specific library services within a library. Service domains can overlap, which introduces the problem of aggregate selection of services. This is addressed by considering similarity, precedence, and restrictions among the services and by defining some aggregation rules. This work mainly focuses on location-based service selection. It is, however, difficult to ascertain the gain as well as user satisfaction of a service with different location boundaries.

Effectively integrating devices and their hosted services in today's smart home depends on a highly inter-operable architecture. The Amigo project [8] aims to develop an AmI architecture for home systems enabling the provision of QoS-aware AmI service selection in the home environment. Shirehjini [24] presented a dynamic, location-aware architecture for media presentation, where an electronic pen and RFID are used to interact with the synchronized 3D view of the user's real physical environment. Mingkhwan et al. [20] proposed a dynamic service composition framework that can incorporate the services and controls provided by appliances within a smart home in a real-time manner. They discussed how the complexity of the service selection process increases as the number of appliances increases and proposed a home network architecture that interconnects with different home appliances and their associated services allowing services to be offered automatically.

Providing services and various entertainment facilities in these frameworks is becoming popular. As new services appear and old services disappear everyday, it is very difficult to select an appropriate service from among similar and heterogeneous services accommodating the dynamic context such as service uncertainty, environment conditions, and finally user satisfaction. In this regard, different selection mechanisms such as dynamic programming, integer programming [25], Dijkstra-based selection [30], genetic algorithms and combinatorial algorithms [31] have been used. However, none of these approaches is directly applicable in selecting services in a smart home monitoring environment. We believe that selecting media services using the ant-inspired algorithm [5] is one of the new ways of service selection, as the ant-inspired algorithm has the ability to adapt to a constantly changing context. In addition, it is distributed and demonstrates robustness to context changes and service uncertainty [14]. Previously, ant-based selection methods have been used for multimedia transcoding service selection based on QoS [11], SOA-based Service Management [4, 14, 22], and conversation based service composition [21]. However, none of these approaches has been used for ambient media service selection.

Chiang et al. [4] proposed a bio-inspired framework for service management in a ubiquitous computing environment where Ant Colony Optimization (ACO) meta-heuristics are adopted for service composition using a simple e-mail application. Musunoori and Horn's [22] research describes an ant-based service partitioning for grid service configuration as a service composition. In [14], basic multimedia services such as streaming services and different transcoding services are composed for service management. The ant-based approach is used to select the most suitable services for the desired composition process.

Our method is consistent with the approach proposed in [12], which presents a gain-based hierarchical service selection using dynamic programming techniques. Using dynamic programming techniques, the author proposed a mechanism that faced a trade-off between gain and cost of a service. Gain is updated based on interaction history, preferences, and context. To update gain, not only is the user context needed to select the appropriate service, but also quality of service (QoS) is required to customize the proper environment. Different QoS parameters may change the user context. To this end, we extend the work by incorporating an enhanced context model based on the well known W^5HH [2] principle, QoS, and ant-based service selection approach to select services in a dynamic context.

4 Proposed ant-based service selection framework

In this section, we present the various components of the system and provide a general description thereof. First, we give an overview of the high level architecture of the system in Section 4.1. Next, in Section 4.2, we describe the mathematical model for user context analysis and preference update in a dynamic situation based on mood, time, activity, companionship, and so on. Lastly, in Section 4.3, we present the ant-based service selection approach and the algorithm for finding the best path in a set of services.

4.1 High-level architecture

Figure 1 illustrates a high level overview of the proposed system, where an ant-based service selector is used to select the optimal composition of services by considering the user's current as well as previous context history. In this system users have a multi-modal interaction facility to interact with the system. Users can interact using their smart phones, touch pads, or laptops. When a user is visible in the environment, the system presents him with different services based on his current context and previous interaction history. To determine the current context, the system uses various sensors, including a camera, temperature sensor, humidity sensor, and motion sensor, installed in the environment. A context controller module is responsible for determining the current user context based on the data collected from these sensors. For example, if a person arrives in front of an entrance door the motion sensor activates the camera to recognize the person and later sends the verified person's identification number to the context controller to determine the context. The context controller uses the current room temperature from the temperature sensor, humidity from the humidity sensor, time from the system clock, and user preference data from the database to calculate the user's current context. To obtain a user specific service, users have the facility to customize various aspects of their preferences such as favorite movie, favorite actor, and so on. This information is stored in the database for future use. The system uses this information to select suitable services in determining the best target composition of services

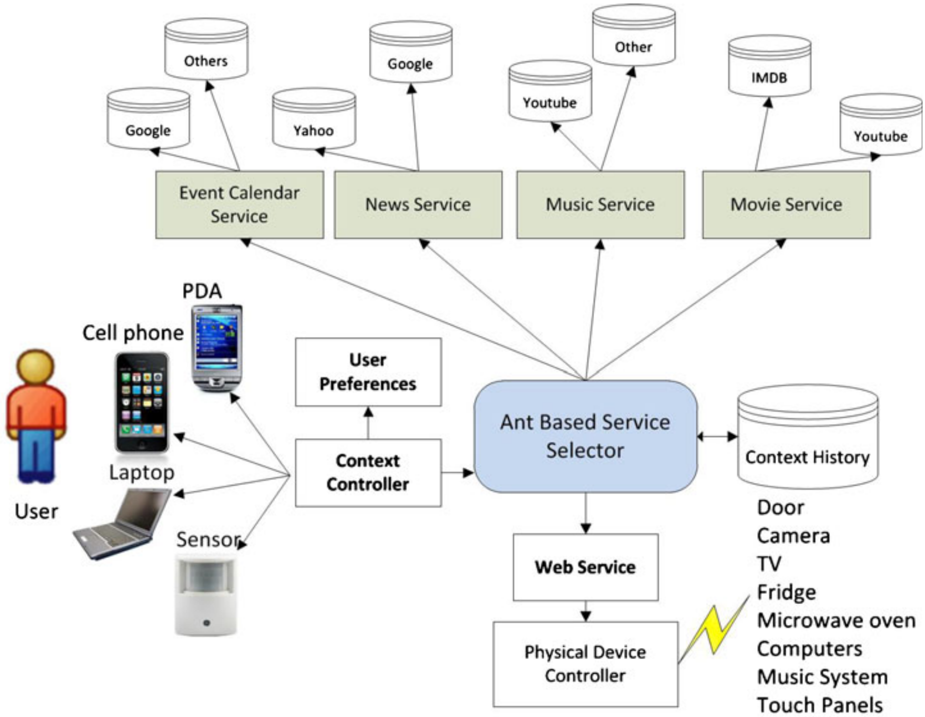


Fig. 1 High-level architecture of our proposed ant-based service selection framework

As can be seen in Fig. 1, different online and off-line services are connected to a centralized ant-based service selector. The primary objective of this selector is to select the best service path based on both user context and Q_oS. User context can be obtained from the past interaction history that is stored in a repository as AUMP. Based on the interaction history in a particular context, a user's preferences are updated to calculate more effective results in the future. A physical device controller acts as a home gateway between different online and off-line services. Different physical devices such as X10 [29], RFID [28], and sensors are connected to this gateway. The high level architecture and its different components are discussed in the subsequent sections.

4.2 User context model

In this section, we present a mathematical model, which is used to select and update the user context. User context depends on different factors such as the user's current mood, appearance, activity, and so on. In addition, the environment context is affected by the temperature, day of the week, room lighting conditions, and so on. As far as context analysis is concerned, we have adopted the popular W^5HH [2] method for extracting the characteristics of a particular user context.

Practically, perfect user context determination is not possible, although the W^5HH principle can be used to determine the required data that needs to be

Table 1 W^5HH Principle

What will be done (activity)	Working, reading, sleeping
When will it be done	Weekday, weekend, morning, evening
Where will it be done	Indoor, outdoor, home, office, bed room
Who is responsible (with whom)	Parents, friends, children, family, alone
Why (in what mood)	Happy, sad, anger, grief
How the job will be done (how long)	Ten minutes, one hour
How much of each resource is needed	Light, volume, air conditioning

extracted in the current user context. Table 1 illustrates questions related to W5HH for context determination. The total user context value is calculated using (1), where $W(What, When, Where, Who, Why)$ and $H(How)$ represent the seven questions for determining context.

$$C_x = \prod_{i=1}^{5} W_i \times \prod_{j=1}^{2} H_j \tag{1}$$

4.2.1 AUMP score update

Our system calculates a set of preferences for a user according to his/her varying context, which we refer to as the AUMP. Similar to our previous work [12], the AUMP includes the scores of metadata-related attributes of various types of media services. This score refers to the user preference for the various attributes of a media in a particular context. Figure 2 shows the structure of the AUMP with user preference in a particular context. The first level of this figure shows different media types such as movies, music, images, and RSS feeds. For each media type, the AUMP includes scores for each attribute of the media. Thus, in the next level, we further divide each media type into its attributes. Each attribute is then subdivided into dataitems. For example, the movie type has genre, actor, actress, and director attributes. Moreover, the genre attribute of music includes Jazz, Rock, and Pop dataitems. Each dataitem has a score in the range 0 to 1. The total score for a specific attribute is always 1. For example, the dataitems for the movie genre attribute are *horror*, *action*, *comedy*, and *animation* and if the scores for the first three dataitems are 0.5, 0.2 and 0.1, respectively, then the last dataitem score must be $1 - (0.5 + 0.2 + 0.1) = 0.2$. Each dataitem is initialized with a score generated automatically by the system or explicitly set by the user. To cope with the varied

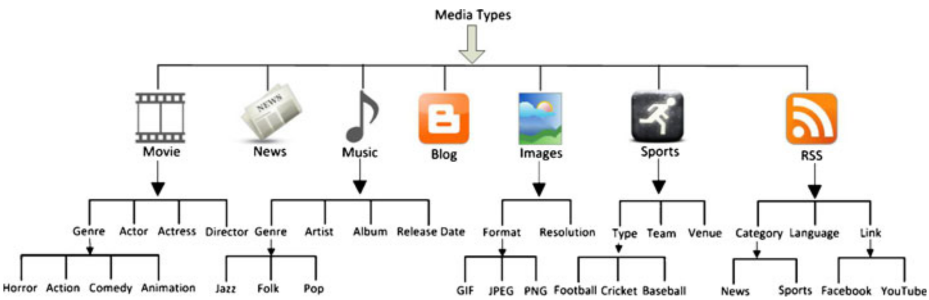


Fig. 2 Ambient user media preference (AUMP) structure

media preferences of a user in different contexts, we consider user context history to update the AUMP score. Let us consider how AUMP is recomputed in media selection in a particular context such as watching a movie during the weekend alone at home.

Let an arbitrary attribute have n dataitems, A_i, denoted as: $A_1, A_2, \ldots, A_n$. At any instance any of the dataitem scores can be changed by the user or the system itself. Let the updated dataitem score and previous score be $A'_i(t)$ and $A'_i(t-1)$, respectively, with $1 \leq i \leq n$. The remaining dataitems are affected by this updated dataitem score as the total score is always the same. We calculate the score for each remaining dataitem by multiplying its current score by the ratio of the total score of all dataitems excluding the current selected item at time t to the total score of all dataitems excluding the current selected item at time $(t-1)$. We compute this ratio (h) using (2). In this equation, C_x represents the score in a particular user context.

$$h = \frac{1 - A'_{i,C_x}(t)}{1 - A'_{i,C_x}(t-1)} \tag{2}$$

So, the score for each remaining dataitem other than the current selected item is given by:

$$A_{i,C_x}(t) = \frac{A_{i,C_x}(t-1) \times [1 - A'_{i,C_x}(t)]}{1 - A'_{i,C_x}(t-1)} \tag{3}$$

If we normalize (3) using (2) we can write the AUMP(A_i) as:

$$A_{i,C_x}(t) = A_{i,C_x}(t-1) \times h \tag{4}$$

4.2.2 User satisfaction estimation

Based on the updated AUMP scores in (4), we compute the user satisfaction scores of the media services using (5) and (6). Equation (5) is based on the AUMP only, while (6) is based on the AUMP and QoS. Here, we describe user satisfaction estimation, as illustrated in Fig. 3. First, we consider the AUMP scores using (4), and then we compute user satisfaction based on these AUMP scores.

(a) *User satisfaction based on AUMP*:

$$U_{i,A_i} = \sum_{j=1}^{n} A_j W_i \tag{5}$$

Where A_j is the dataitem of an attribute or AUMP score computed using (4) and W_j is the relative weight factor of A_j.

(b) *User satisfaction based on AUMP and QoS*:

$$U_{i,A_i,Q_i} = \beta \times U_{i,A_i} + (1-\beta) \times Q_i \tag{6}$$

Where, U_{i,A_i,Q_i} is the user satisfaction in using the media service based on U_{i,A_i} and QoS. β and $(1-\beta)$ are the relative weight assigned to U_{i,A_i} and the QoS metric Q_i . The value of β depends on the importance of U_{i,A_i} and the QoS metric Q_i. If $\beta = 1$, we ignore QoS and allocate total importance to U_{i,A_i} resulting in (5).

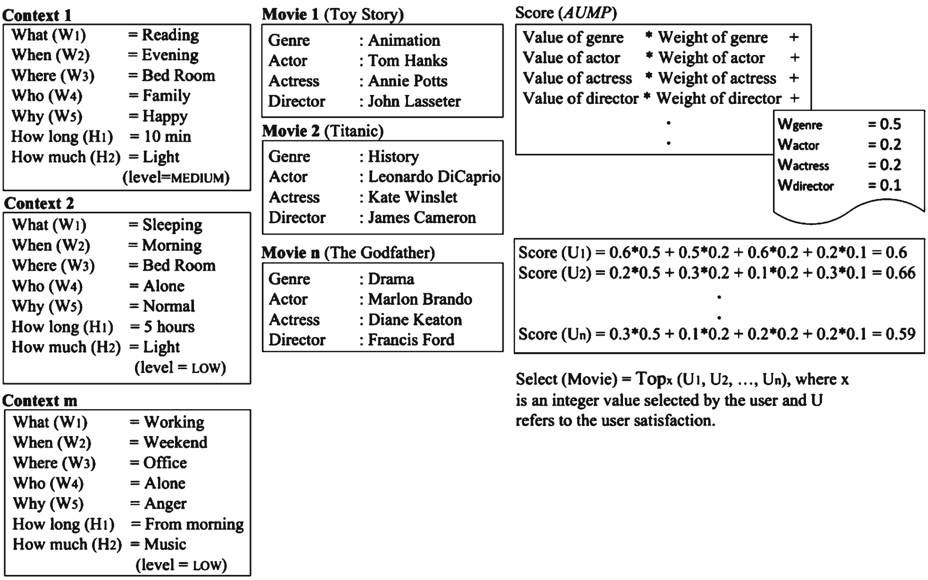


Fig. 3 Changes in AUMP scores after using the movie service in a particular context

4.3 Ant based service selection

Let us consider a media service network (S, L), where S is the set of service nodes and L is the set of links. Each link is associated with a positive n number of user satisfaction scores. The ant-inspired media service selection problem is defined to find a suitable media service path from the number of services such that the overall satisfaction of a user given by (6) is maximized subject to the constraints $\sum_{i=1}^{n} d_i \leq D_{\max}$. The next media service is selected based on the probability P_i of choosing services according to (7). This selection decision is actually based on the local pheromone value (φ) and user satisfaction score. The pheromone values are initialized to $\frac{1}{N}$ towards a destination column.

During backward phases, as stated in the algorithm, the pheromone value is updated using (9). If all neighbors have been visited, the probabilities of all the neighbors are equal. U_i is updated as the user satisfaction value of the selected service node (U_δ) divided by the sum of all the user satisfaction values (U_j) of the neighboring service nodes times the number of neighbors minus 1, as shown in (8).

$$P_i = \frac{\varphi_i + \alpha \times U_{i,A_i,Q_i}}{1 + \alpha \times (N-1)}, \ 0.2 \leq \alpha \leq 0.5 \tag{7}$$

$$U_i = \frac{U_\delta}{\sum_{j=1}^{N} U_j} \times (N-1) \tag{8}$$

$$\varphi_i = \begin{cases} \varphi_{i-1} + \Upsilon \times (1 - \varphi_{i-1}), & Selected\ service \\ \varphi_{i-1} + \Upsilon \times \varphi_{i-1}, & Non - Selected \end{cases} \tag{9}$$

Algorithm 1: The Proposed ant-based ambient media service selection

```
Forward-Ant(source-node, current-node, destination-node);
begin
    if destination media service node is reached then
        Create a new Backward-ant and copy forward-list to backward-list;
    else
        Add current-node to forward-list;
    if Selected service nodes are not yet visited then
        Choose the next neighbor nodes according to the following
        probability P_i = (φ_i + α×U_i) / (1 + α×(N−1)), 0.2 ≤ α ≤ 0.5;
        if selected neighbor visited then
            choose another neighbor service node;
    else
        Perish Forward-Ant;
end
Backward-Ant(source-node, current-node, destination-node);
begin
    if source is reached then
        Perish Backward-Ant;
    else
        for all neighbor nodes do
            if selected neighbor node visited by Forward-Ant then
                φ_i = φ_{i−1} + ϒ × (1 − φ_{i−1});
            else
                φ_i = φ_{i−1} + ϒ × φ_{i−1};
            Remove first item of Backward-list
        Move Backward-Ant to selected neighbor node
end
```

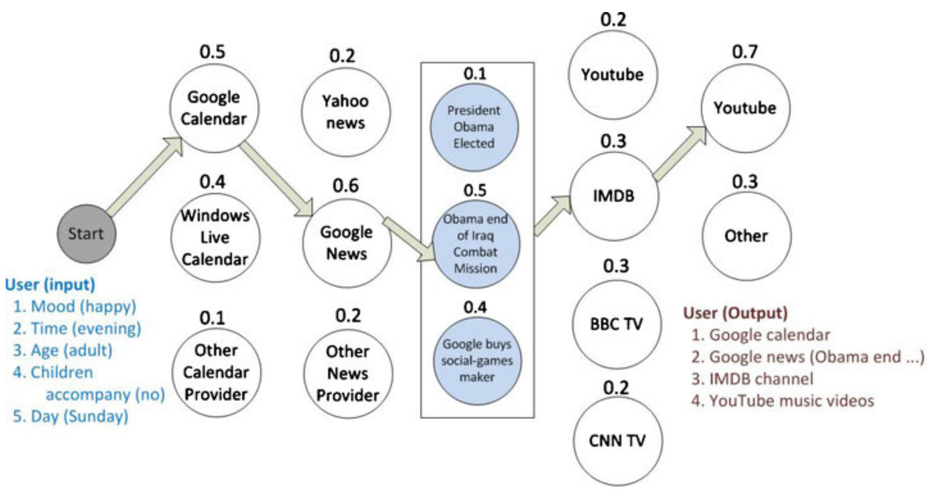


Fig. 4 Selection of multiple services based on the user satisfaction score

Algorithm 1 gives a high level description of the ant-based media service selection algorithm that is used to select the best suited services for users. Given the initial AUMP scores by the user, the system stores these scores in the database and updates the scores based on the context and user interaction history. In each step, the final user satisfaction score is calculated based on the updated AUMP scores and the QoS as described in (6). While calculating the user satisfaction, the system constructs a network like that in Fig. 4, in which the ant-based selection approach discovers the media service nodes in the network and finds the most suitable path based on the user satisfaction as described above. This service network has a list of nodes, with each node representing a media service (like Google calendar service, BBC TV broadcasting service, and so on). As mentioned before, each node has a user satisfaction score assigned by the system and based on the AUMP and QoS. In Fig. 4, the most appropriate service for the user is depicted by arrows. According to the figure, for an adult user in a happy mood on a Sunday evening without any accompanying children, the preferred services are Google calendar, news from the Google news service, movies from the IMDB movie service, or music videos from the YouTube video service.

5 Implementation and result

This section describes the implementation details of the prototype that reflects the framework presented in Section 4. Microsoft $C^{\#}$ version 8.0 and the SQL server 2005 database server were used to develop the prototype system. In the following, Section 5.1 describes the experimental setup and the different devices that are connected within the environment, while Section 5.2 briefly discusses the development of the different services and modules.

5.1 Environment setup

This section describes the experimental setup in our laboratory environment in the context of a smart home monitoring environment. Figure 5 shows the layout of the environment where different devices are connected to each other to provide services based on the user context and preferences. In addition, all the networked devices are connected to a wireless router. The necessary equipment to control the devices is installed in the control room. To capture context data, we used multiple sensors including a camera, motion sensor, humidity sensor, RFIDs, as well as the user log data as described in our earlier work [15]. Camera and sensory devices were installed in three different rooms in the test environment. In this environment, all the rooms were equipped with an X10 [29] lamp allowing the user or system to control the lighting level. For real-time face recognition we used a high definition Microsoft *LifeCam* 3.0 camera, which operates based on the face recognition algorithm implemented in OpenCV [16]. *X*10 *Pro Occupancy* motion sensor and *Sharp IR* distance sensor were attached to the camera to provide the ability to capture images from certain triggered events. These events were triggered by monitoring the microphone sound as well as the motion tracking IR devices.

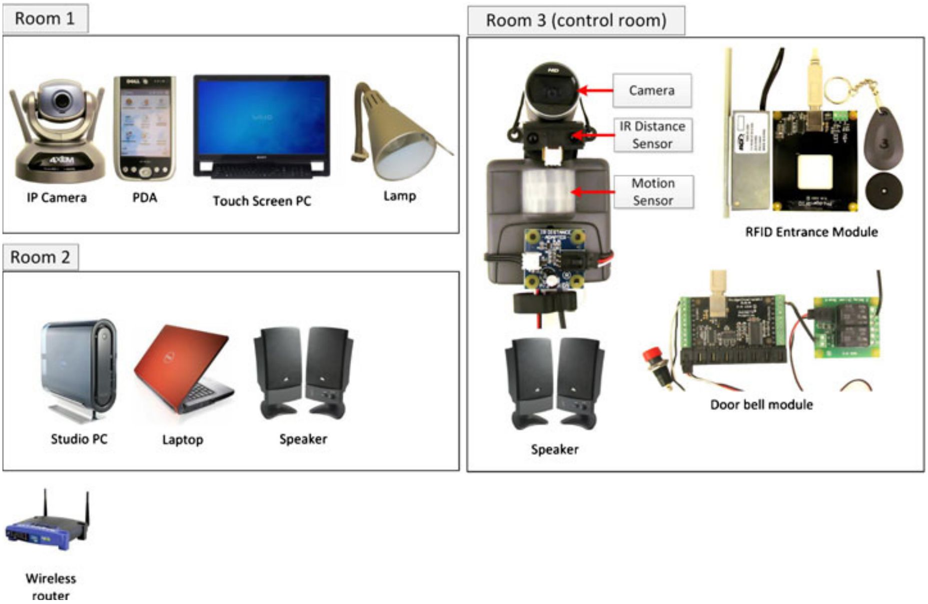


Fig. 5 Layout of the experimental environment

5.2 Development of different services

In our implementation, we adopted a web service based design approach. In this section, we briefly discuss the design of different services and components such as the user context controller, AUMP management service, ant-based service selector, media renderer, physical device controller, and RFID reader.

5.2.1 User context controller

The user context controller depends primarily on the Ubisense [26] Location Driven Training (LTD) solution and OpenCV [16] face recognition system. The former system collects data from a sensor network throughout the area being monitored. All sensors are standard IP based devices connected using standard network equipment, which are monitored and tuned in real-time. Each person wears a compact Ubisense tag, enabling him/her to be located automatically when entering the environment, with the data passed through the Ubisense API. Our system uses this API to receive the real-time user location information within the environment. Later the system also attempts to process the face image captured by the camera and finally calculates the context information. It should be noted that during the context calculation, the system also keeps track of the time of the calculation, day of the week, who is around, and current mood of the user based on a facial expression analysis.

5.2.2 AUMP management service

As mentioned in Section 4, we maintain user interaction history to dynamically update user media preferences, which we call AUMPs. We have written a method in $C^{\#}$ and published it as a web service (WS) so that it is available to other services. We have also developed another WS, which accumulates the updated AUMP score from this method, and calculates the user satisfaction value based on the accumulated AUMP score and QoS using (5) and (6). It should be noted that the estimated user satisfaction is used by the ant-based service selector to recommend to the user the media with the highest score.

5.2.3 Ant based service selector

We implemented the ant-based media service selection algorithm presented in Section 4.3 as a $C^{\#}$ web method so that other modules can have access to this method. The method uses the updated user satisfaction to construct a media service network similar to that shown in Fig. 4. This method also produces the final list of services and the associated items based on the input and AUMP.

5.2.4 Media renderer

The media renderer service in our design has been implemented using VLC [27]), which is a highly portable multimedia player supporting various streaming protocols, audio, and video formats. VLC integrates a small HTTP server that can be used for a HTTP remote control interface. We developed a WS wrapper to control the VLC player using the VLC HTTP interface.

5.2.5 Physical device controller

The physical device controller controls the physical devices. Each physical device is connected to a valid X10 [29] module, with each module having an address that can be uniquely identified within the smart environment. X10 is an old but popular power line communication technology primarily for controlling home electronic devices such as lights, fans, TV, music system, etc. The physical device controller controls the X10 modules using the X10 active home script library and web services dynamic discovery (WS-Discovery) protocol. WS-Discovery is a multicast discovery protocol defined with the purpose of allowing dynamic discovery and advertisement of target services in order to find a specific service. The service can query the network using multicast search messages and services. In our prototype, we also used web service eventing (WS-Eventing), which is a web service protocol that describes how a client (subscriber) can register for certain events (subscriptions) of a web service (event source). Thus, changes in the service can be notified to any client without requiring a standard polling mechanism. If any device wants to connect to the web service, it is required to send a multicast message to search for target services. In reply it sends a unicast response to the sending client if the target service matches a probe message.

5.2.6 RFID reader

In our prototype, an RFID reader is installed in the main entrance (see Fig. 5). The reader can send or receive data when displaying an RFID tag to the reader. We developed a web service to receive the data from the RFID reader through the ActiveHome PC interface.

5.3 Evaluation and results

To evaluate the prototype and to verify the suitability of our proposed approach, we first show the user interface of the proposed framework in Section 5.3.1, followed by highlights of some of the performance analyses in Section 5.3.2. Finally, we present the results of user studies with real users in Section 5.3.3.

5.3.1 User interface for the prototype system

Figure 6 demonstrates the user interface for the developed PDA-based prototype, which is used to interact with the system. The initial screen, Fig. 6a, depicts the user preference settings for different attributes. As mentioned before, the total score for a particular dataitem is always equal to one. When a user enters a value for an attribute, the other attribute values are adjusted in such a way that the total score remains one. Moreover, the system automatically assigns initial values to the attributes, if users fail to supply the values. Figure 6b shows the detected device list. The prototype has a built-in feature to manage the devices connected to the system. We can view or update the settings or we can disable a device through this interface. Finally, Fig. 6c gives an example of the recommended media services for a user based on the AUMP, and referring to his or her context, previous interaction history, provided preference data, and QoS.

5.3.2 Performance analysis

When a user selects ambient media over a period of time, the interaction history is kept in the interaction history repository, and is then used to update the AUMP scores. Based on the interaction data, the scores are updated using (4).

(a) Preference Settings (b) Devices (c) Services

Fig. 6 User interfaces for the prototype system on a real Dell Axim X51 PDA

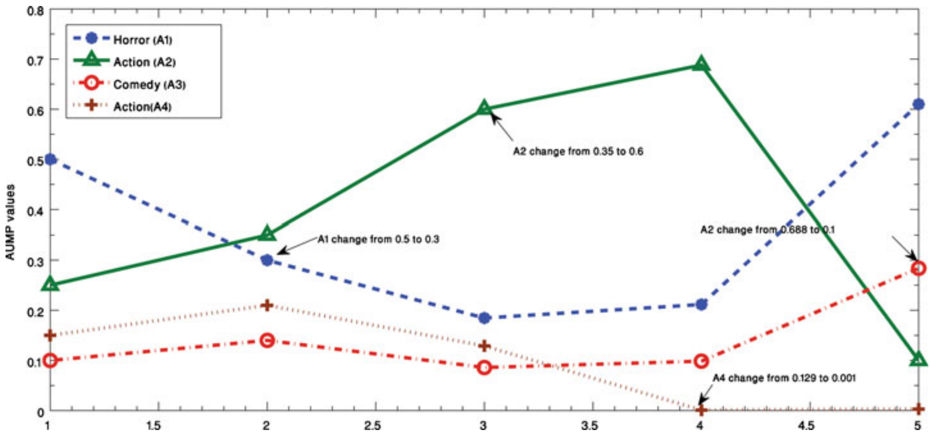


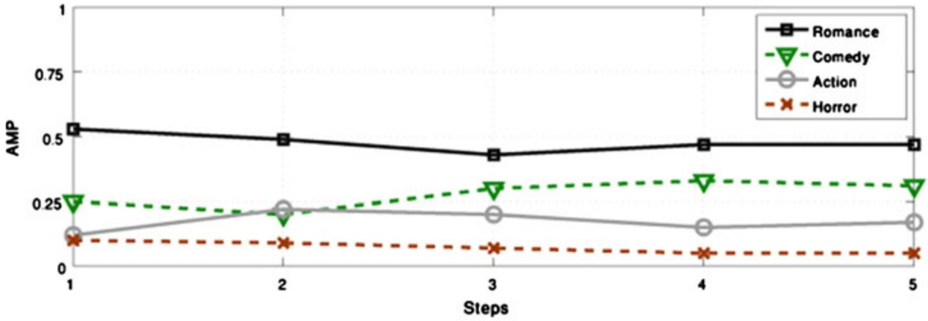
Fig. 7 Dataitem updates for movie-genre attribute based on the dataset listed in Table 2

In Fig. 7, we only show a few AUMP updates for clarity. The scores in the AUMP are updated after each interaction and reflect the changing preference of a user through the various metadata attributes of the media services. For example, when the system changes the AUMP score of *Action* movie from 0.35 to 0.6, all the other dataitems are adjusted accordingly so that the total score in each step remains unchanged. Consequently, if the *Action* movie score changes from 0.35 to 0.6, *Horror* ($A1$) changes from 0.3 to 0.1846, *Comedy* ($A3$) from 0.14 to 0.086, and *Action* ($A4$) from 0.21 to 0.129. Therefore, the total score in this step is $0.6 + 0.1846 + 0.086 + 0.129 = 1$, which is the same as the previous total score, $0.35 + 0.3 + 0.14 + 0.21 = 1$.

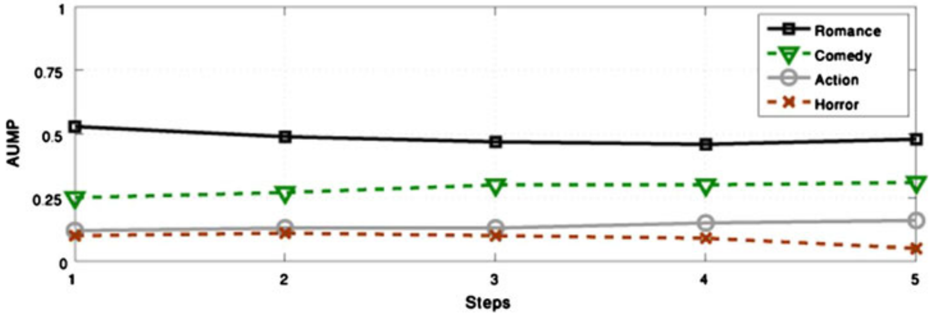
To see how the dataitems change over a number of steps, we performed a comparative experiment in which we randomly selected four movies from different movie-genres (*romance*, *comedy*, *action*, *horror*) and a user arbitrarily provided initial values for the dataitems. As shown in Fig. 8, the first values in each movie genre represent the initial scores provided by the user. Figure 8a and b demonstrate the results of our previous work [12] and the prototype, respectively. From Fig. 8b, it is clear that the changes in AUMP score over time (steps) are more constant

Table 2 Dataitem update for movie-genre attribute

Data items	Horror A_1	Action A_2	Comedy A_3	Action A_4	h (2)
Initial values	0.5	0.25	0.1	0.15	
A1 change from 0.5 to 0.3	0.3	$0.25 \times 1.4 = 0.35$	$0.1 \times 1.4 = 0.14$	$0.15 \times 1.4 = 0.21$	$\frac{1-0.3}{1-0.5} = 1.4$
A2 change from 0.35 to 0.6	0.1846	0.6	0.086	0.129	$\frac{1-0.6}{1-0.35} = 0.61$
A4 change from 0.129 to 0.001	0.2117	0.688	0.0986	0.001	$\frac{1-0.001}{1-0.129} = 1.14$
A2 change from 0.688 to 0.1	0.61	0.1	0.284	0.00288	$\frac{1-0.1}{1-0.688} = 2.88$



(a) Results based on our previous work



(b) Results based on the proposed system

Fig. 8 Comparative results of our AUMP based method and our previous work

(horizontally flatter) than those in Fig. 8a, which indicates that the preference level over time is more appropriate in Fig. 8b than in Fig. 8a. It is not realistic for a user to provide a high score for a particular dataitem and the system to increase or decrease the value based largely on the context. It is better to minimize the different AUMP scores at each step. As a result a smoother result is expected.

To test the performance of our ant-based service selection algorithm described in Section 4.3, we conducted an experiment in which we used five different media service types (movie, news, music, image, RSS). For each media service type there

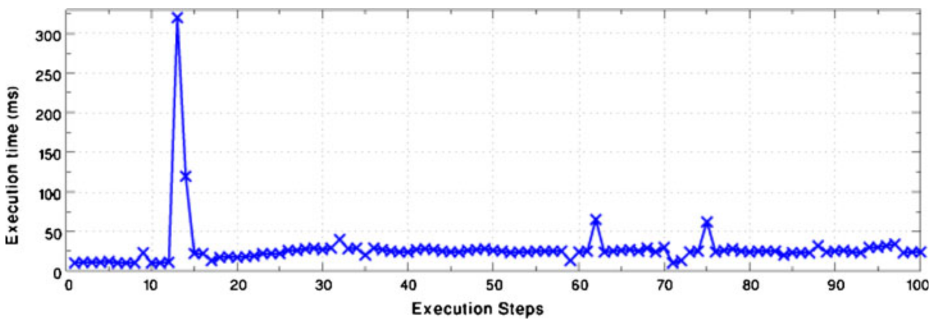


Fig. 9 Execution time of the ant-based algorithm over 100 executions

Table 3 Usability questionnaire

#	Question
Q_1	Easy to interact with the system?
Q_2	Consider using the system at your home?
Q_3	Perceived delay between the system and the service responses was acceptable?
Q_4	It was easy to enter the preference choices into the system?

were different services (e.g., IMDB, YouTube, and local database services). In the experiment the number of search results was limited to a maximum of 20.

Finally, we applied our ant-based selection algorithm to select a suitable service for the target user. We executed the same algorithm 100 times and listed the results. As shown in Fig. 9, we found that the average execution time of the selection algorithm is approximately 25 ms, although some of the iterations showed unexpected execution times. This is due to the Internet speed and server load during execution.

5.3.3 Usability study

Prior to conducting the usability test we designed a test plan, where we defined our evaluation objectives, developed questions for the participants, identified the measurement criterion and decided upon the target users of the system. The test took place in our university laboratory with 12 volunteers comprising different age groups. Six of the participants were in the age group 18–36, three of them were in the age group 13–18, and the remaining three were in the age group 36+. Initially, the volunteers were asked to provide their media preferences. The users were permitted to access the system in the test environment for a week. Thereafter, interaction history data was collected. The users' activity was monitored throughout the experiment and recorded for analysis. Later, based on their interaction experiences, the users completed a questionnaire (listed in Table 3), where they were requested to provide ratings for the difficulty, likeability, delay, and ease of use of the system.

As shown in Fig. 10, the user responses are shown on a Likert five-point scale [17] where the higher the rating is, the greater is the satisfaction. Feedback from the

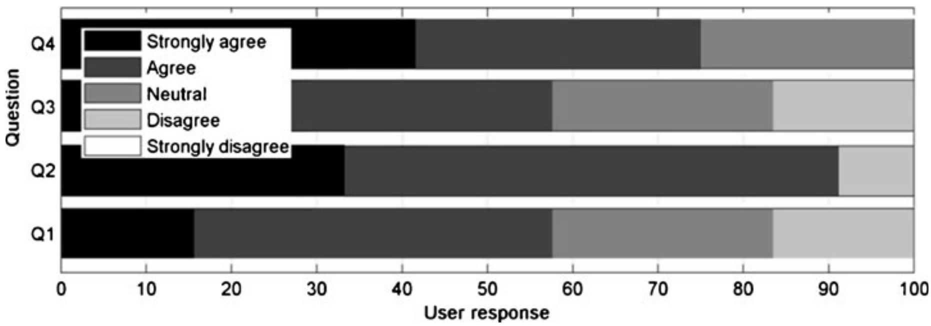


Fig. 10 User responses to the usability test questions listed in Table 3

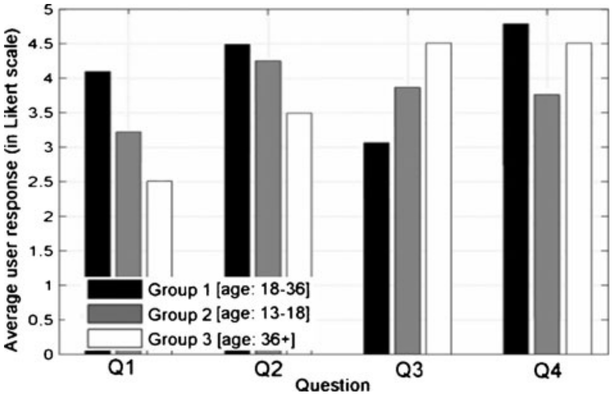


Fig. 11 Comparison of the responses of users from different age groups

users was summarized and the average of the user responses calculated. It is worth mentioning that more than 90% of the users would like to use our ant-based service selection prototype at their homes. Overall 82% of the users were also satisfied with the delay between the system and service responses. Table 3 summarizes the overall performance scores of the users. The higher mean values for likeability and ease of use represent a very satisfactory user response, while the moderate mean values for delay and difficulty show relatively good user satisfaction.

During this study, we also attempted to evaluate the acceptability of the system by the users from different age groups. We divided the users into three age groups, namely group1: ages 18–36, group2: ages 13–18, and group3: ages 36+ and recorded their responses, as depicted in Fig. 11. Compared to the older group of users, users from the younger group seem to be more eager to use the system.

6 Conclusion

In this paper, we presented a media service selection framework for smart home monitoring using an ant-based service selection approach. As available media services may have similar functionality, but different user satisfaction and preferences, the challenge is to find the best way of selecting appropriate media services that fulfill the user's needs while considering the surrounding context. To this end, the proposed framework uses the potential of the ant-based service selection approach by considering user satisfaction, which is the key factor for media service selection. User satisfaction is based on the AUMP and QoS metrics. The proposed framework was validated through experimental results. In future, we aim to evaluate the system further to measure the performance of the system with a large-scale dataset. We believe that the proposed approach for the media recommendation and service selection framework will introduce a new direction in AmI.

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