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Context-Aware Media Personalization

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Abstract. Personalizing the user's media experience based on his changing context, which we call context-aware media personalization, is an important challenge. Unlike traditional personalization systems that merely based on user preference, context-aware personalization system takes context information ranging from user preference and situation to device/network capability as input for both content and presentation recommendation. This paper introduces the generic architecture of context-aware media personalization, and presents solutions for the key techniques of it, which are MPEG-7 based media description model and ontology based context representation model, context aggregation, reasoning, and learning, media recommendation, and media adaptation.

Introduction

With rapid development of digital media technologies, more and more media contents are being used for the purposes of commerce, education, and entertainment. On the other hand, advances in communication and microelectronics have led to a shift from traditional computer-centric to human-centric information access mode, which is known as *Pervasive Computing*. It allows a person to use a variety of pervasive end devices, such as personal computer, PDA, and hand phone, to access media contents. The combination of these two trends holds the potential of providing a user with seamless and ubiquitous access to rich media resources. However, there are several new technical challenges for effective and appropriate content delivery to users in pervasive computing environment: (a) different users may have different needs; (b) pervasive end devices usually have various capabilities; (c) the heterogeneous networks lead to a dynamic distributed computing environment.

Therefore, media applications should recommend the right content, in the right form, to the right person according to the user's preferences and his current environmental information. An important technique to address the aforementioned challenges is *context-aware media personalization*, i.e. customizing media content based on the user's changing context. Compared to the traditional media personalization, context-aware media personalization provides a solution to address the media personalization in pervasive computing by incorporating context information into recommendation process. It accomplishes both content and its presentation recommendation adapting to user's context and environmental characteristics. In this paper[1], we introduce the generic architecture of context-aware media personalization, and present solutions for the key techniques of it.

1. System Architecture

The context-aware media personalization system consists of seven collaborating components, as shown in Figure 1. The content and corresponding metadata are stored in the media content base and metadata base, respectively. Context acquisition, reasoning and learning aggregates basic context from various sources, infers high level context from basic sensed contexts, and deduces user preferences using implicit machine learning techniques. The contexts are all stored in the context knowledge base. The media recommendation queries context information and media description from the context knowledge base and metadata base respectively. It estimates the score for media content and determines its appropriate form in a particular context. If the recommended item has already the variation in appropriate form, it calls the media delivery directly; otherwise it first invokes the media adaptation to make adjustment, and then calls the media delivery.

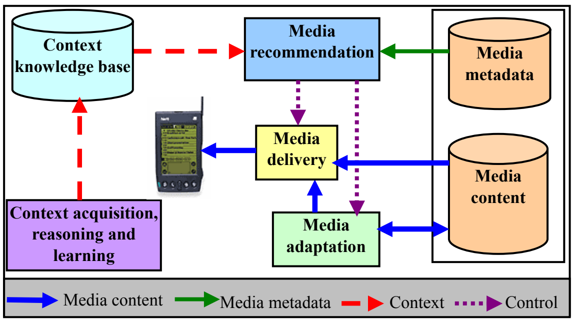

Figure 1. System architecture

2. Representation Model

The MPEG-7 *Creation DS* and *Classification DS* are used to describe information about the media item, such as the title, keyword, director, actor, genre, and language. This information is used to match user preferences. The *Variation DS* is used to specify variations of media content as well as their relationships. The *Variation DS* plays an important role in our context-aware media personalization by allowing the selection among the different variations of the media content in order to meet the specific capabilities of the terminal devices and network conditions.

For efficient processing, we classify the context into three categories: preference context, situation context, and capability context. An ontology-based context model is designed for context representation. In the modeling approach, OWL (Web Ontology Language) [1] is adopted as representation language to enable expressive context description and data interoperability of context.

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3. Context Acquisition, Reasoning and Learning

Context acquisition observes basic or low-level context, e.g. location and time, from an array of diverse information sources via hardware sensors or software programs. We deployed various hardware sensors in our prototype system, including location sensors, lighting sensors, microphones, and video cameras. We also developed some software programs to capture context, e.g. GUIs for explicitly inputting user preferences and daily schedule; observers for capturing user feedback to a specific content; monitors for detecting terminal capabilities and network characteristics.

Context reasoning infers high-level contexts from basic sensed contexts, resolves context conflicts, and maintains knowledge base consistency. To support various kinds of reasoning tasks, we can specify different inference rules, and preload them into the appropriate logic reasoner. We adopted a rule-based approach based on first-order logic for reasoning about contexts. Our current system applies Jena2 generic rule engine [2] to support forward-chaining reasoning over the OWL represented context.

Context learning implicitly deduces and updates user preference by utilizing user feedback to a specific show or user viewing history. We propose a collaborative context learning approach based on Master-Slave architecture, of which master device is a device with strong capabilities, such as PC, and slave devices are pervasive terminals with limited resources. The preference learning and update is done in the master device by utilizing overall user feedback information collected from different devices as opposed to other traditional learning methods that just use partial feedback information in one device. The slave devices are merely responsible for observing user behavior and uploading feedback information to the master device. Details of the centralized user preference learning strategy were described in [3].

4. Media Recommendation

The recommendation process consists of four steps described as follows:

(1) Evaluates between media items and preference context by adopting VSM described in [4]. We model both the multimedia content and user preference as vectors. The *cosine value* of the angle between the two vectors is adopted as similarity measure between media item and preference context. The larger the *Similarity* is, the more relevant between the media content and user preference.

(2) Evaluates between media items and situation context by adopting Naïve Bayes classifier [5]. We group the values of each situation context dimension into classes. For example, we can divide a user's location into three classes: Living room, Bed room, and Dining room. We evaluate the probability of a media item belonging to a class of a context dimension or a combined situation context, e.g. how much probability of the movie *Gone With the Wind* is viewed by the user in *Bed room*, *P(Bed room|Gone With the Wind)*. Suppose C_1, C_2, ..., C_j, ..., C_k are k classes of situation context considered, the probability of media item $\vec{x}$ belonging to class C_j, that is, $P(C_j \mid \vec{x})$, can be calculated through statistical analysis of user viewing history. Given a class C_j, only the media items that have a high degree of $P(C_j \mid \vec{x})$ would be recommended.

(3) Evaluates between media items and capability context by adopting rule-based technique. The modality, format, frame rate, frame size, etc., of the recommended item must satisfy the capability context. We adopt rule-base approach to infer appropriate

form (such as modality, format, frame rate, and frame size) from capability context.

(4) Measures the global evaluating by synergizing above three approaches. The recommendation output consists of two parts: appropriate form (e.g. modality, format, frame size, etc) and score. The appropriate form is determined by rule-based evaluating on capability context. The score is composed of the *Similarity* between a media item and the preference context (achieved with VSM approach), the *probability* of the media item belonging to the situation context $P(C_j \mid \vec{x})$ (obtained through Bayesian classifier approach). We use a weighted linear combination of these two sub-scores to calculate the overall score, $Score = W_p \times Similarity + W_s \times P(C_j \mid \vec{x})$, where W_p and W_s are weighting factors reflecting the relative importance of preference context and situation context.

5. Media Adaptation

Media adaptation performs content adaptation by using two techniques: summarization and transcoding. Media summarization performs summarizing content (a video or audio) into a short one according to storage capacity, battery power, and user time constrains. Media transcoding conducts transforming the content from one media type to another so that the content can be processed by a particular device or delivered by a specific network condition. Media adaptation can be statically done at authoring time prior to delivery or dynamically done on-the-fly if needed. In our system, both strategies are used. To perform online transcoding of images, we utilize the open source compression/decompression libraries from the Independent JPEG Group (http://www.ijg.org/). The video transcoding is implemented based on the public domain software for H.263.

6. Conclusion and Future Work

In this paper, we identify the generic architecture of context-aware media personalization and present the enabling technologies to realize it. Our future work includes context-aware educational materials personalization, in special, for teaching and learning in higher educational institutions. We believe that our context-aware media personalization technique is applicable for the recent diverse faculty’s teaching contexts and also student’s learning context in higher education.

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