Research on Mobile Library Information Acceptance Scenario Recognition: Postprint

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Abstract

[Purpose/Significance] To overcome the insufficient perception and computing capabilities of ubiquitous computing environments regarding the diversity and heterogeneity of sources inherent in mobile library information reception contexts, thereby achieving a seamless user experience in information acceptance. [Method/Process] Based on context-aware theory, this study employs the Hopfield neural network algorithm to replace context ontology construction and reasoning, thereby developing a mechanism model for mobile library scenario recognition. [Results/Conclusion] This model simplifies the complexity of scenario-based context configuration in mobile libraries, achieving a scenario recognition accuracy of up to 73%.

Full Text

Preamble

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Research on Scene Recognition for Information Acceptance in Mobile Libraries

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Abstract

[**Purpose/Significance**] This study aims to overcome the insufficient perception and computing capabilities of pervasive computing environments regarding the diverse and heterogeneous sources of mobile library information acceptance contexts, thereby achieving a seamless user experience in information acceptance. [**Method/Process**] Based on context-aware computing theory, we employ the Hopfield neural network algorithm to replace ontology construction and reasoning, constructing a mechanism model for mobile library scene recognition.

[**Result/Conclusion**] This model simplifies the complexity of scenario-based context configuration in mobile libraries, achieving a scene recognition accuracy rate of 73%.

Keywords: mobile libraries; information acceptance scenarios; context-aware computing; scene recognition; artificial neural networks
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1. Evolution of Context Awareness for Mobile Library Information Acceptance

1.1 The Evolution of Context Awareness

The concept of pervasive computing was first proposed by M. Weiser in his 1991 article "The Computer for the 21st Century" published in *Scientific American* [1]. Pervasive computing aims to "establish an environment filled with computing and communication capabilities that gradually merges with people," achieving the fusion of information space and physical space along with spontaneous interaction. Pervasive computing has formed many relatively complete research domains, such as smart spaces, wearable computing, context-aware computing, and nomadic computing [2]. With the introduction of scene elements such as big data, sensors, positioning systems, mobile devices, and social media into mobile libraries, the information acceptance context of mobile libraries has become a collection of contextual elements across different dimensions involved in scenario-based services. These contexts exist in mobile library scenes in both implicit and explicit ways, transforming mobile library scenes into functionally immersive spaces [3]. As the dimensions and elements of mobile library information acceptance contexts continue to enrich, adopting universal context computing methods inevitably highlights the high dimensionality of the mobile library context element matrix [4]. To better address this issue, we propose a discrete Hopfield neural network-based computational mechanism model for scenario-based context awareness in mobile libraries, which further integrates and fuses information acceptance contexts into user-required scene context sets [5]. This model avoids problems such as context database explosion, cumbersome reasoning rules, and design difficulties [6]. To verify the effectiveness of the proposed mechanism model, we employ neural network computing methods to recognize scenes effectively based on user perception of contextual efficacy across different dimensions. For example, when a user is handling an urgent task and receives a phone call, the mobile library collects scenario-based information acceptance contexts, fuses these contexts to determine that the user is in an urgent and busy state, and automatically replies if the call's urgency level is not high.

1.2 Current State of Context Awareness

Mobile library information acceptance scene recognition relies on context awareness, which essentially involves mining context configurations that meet user expectations for information acceptance. This configuration process is closely related to context perception. Mobile library scenario-based context-aware computing involves multiple aspects, including the association and coupling of contextual elements across different dimensions. T. Lemlouma et al. [7] discussed content adaptation for mobile devices, defining and using a device-independent model to achieve automatic content adaptation based on semantics and target device capabilities, implementing services in the form of SOAP services through XQuery language queries. A. Bottà et al. [8] proposed a context adaptation model based on fuzzy rules using evolutionary algorithms, constructing a new indicator system through fuzzy ranking relationships and developing a multi-objective evolutionary algorithm to achieve context adaptation accuracy based on Pareto optimal solutions for mobile library scenario-based information acceptance scene recognition. Z. Lei et al. [9] found that in pervasive computing applications, computers embedded in devices are used for control tasks; however, current information sources contain rich media data unsuitable for resource-constrained devices. In summary, existing research suffers from several limitations: (1) Poor adaptability flexibility. Current applications require system developers to achieve flexible adaptation between dynamic scene-based information acceptance contexts and user information acceptance during initial system design, which becomes overwhelming given the vast diversity of scenes. (2) Complex context reasoning. When scenes involve numerous contextual dimensions with complex element relationships, rule formulation and maintenance become extremely cumbersome, affecting both response time and recognition accuracy. Since not all contexts in different scenes are effective—manifesting as a binary phenomenon where contextual utility is either 1 or -1—this aligns precisely with the binary neurons of discrete Hopfield neural networks. Based on this understanding, we propose a scene recognition concept using discrete Hopfield neural networks to fuse raw contextual data into scenario-based context datasets, ecologically adapting to evolving user information needs.

2. Context Awareness Patterns for Mobile Library Information Acceptance

2.1 Context Awareness Path

In the era of mobile scenarios, intelligent mobile terminals feature numerous built-in sensors with powerful capabilities for collecting user and context state information [10]. The status of contextual elements collected by mobile library terminal sensors and positioning systems can be represented by corresponding variables. At a given moment, mobile library contextual elements can be expressed as an n+1 dimensional vector C={C, C_0, C_1, ···, $C_{\ 1}$} (where n N). If vector A={A_0, A_1, ···, $A_{\ 1}$} (where m N) represents combinations of mobile library scenario-based information acceptance behaviors such as searching, downloading, and browsing, then the pervasive computing system model essentially establishes the mapping relationship C→f(A). However, most existing mobile library contexts are not fully utilized within a user' s specific timeframe. Directly adapting raw contexts to user information behaviors is cumbersome, time-consuming, and inefficient [11]. If $S=\{T, C_0, C_1, \cdots, C_{\ 1}\}$ represents the state set of different contextual dimension elements for a user in a particular scene, the mathematical modeling approach for mobile library information acceptance context-aware computing is: $C \to f_1(C) \to f_2(A)$. This context modeling approach not only aligns with the actual service mechanism of mobile libraries but also conforms to human information behavior habits and development design logic, reducing development difficulty [12]. We introduce a scenario-based adaptation expressed as S_{adaptation}={C, f, A}, where C represents the set of relevant contexts in a scene, A represents the set of user information acceptance behaviors in that scene, and f represents the mapping relationship between sets C and A. Mobile library scenario-based context awareness inherits the essence of pervasive computing, replacing context-driven with scene-driven approaches as an extension of pervasive computing. Scenes contain both the basic context set characterizing a scene and the set of actions executed by the system based on user information acceptance behaviors in that scene. Mobile libraries can use algorithms to filter, clean, integrate, aggregate, and fuse different raw contexts into various scene context sets [15], ultimately completing the "context-user-scene" mapping adaptation.

2.2 Context-Aware Computing for Mobile Library Information Acceptance

User willingness for information acceptance often exhibits persistence, assuming that within a certain period, user information acceptance willingness remains unchanged. For example, when a user enters a physical library, the mobile library analyzes historical data and sends reminders when the user walks to frequently browsed book classification areas [13]. Current context-aware research primarily focuses on context organization; however, when initial context organization fails to meet mobile library users' information acceptance expectations, context reorganization becomes necessary [14]. For mobile library context-aware computing, it is essential to refine both mobile library scene contexts and user information acceptance for subsequent adaptation. The binary nature of discrete Hopfield neural network neurons—where outputs take only values of 1 and -1—reflects whether contextual elements across different dimensions are activated or inhibited in a scene. The inhibition or activation states of different information acceptance contextual elements are adapted according to corresponding scene function adaptation rules, with the fusion process accomplishing the entire mobile library information acceptance scene recognition.

3. Mobile Library Information Acceptance Scene Recognition Mechanism

3.1 Scene Recognition Framework

The ultimate goal of mobile library information acceptance context awareness is to dynamically identify user scenes and configure contexts reasonably based on historical data of user scene information acceptance [16]. To this end, we adopt a hierarchical structure to describe the mobile library scene-driven context-aware computing system. According to the mobile library scene recognition process, scene recognition can be divided into four layers: physical layer, context basic layer, scene abstraction layer, and application layer. These four layers collaborate to complete context-aware scene recognition. During scene recognition, threshold adaptation is performed for contextual elements across various dimensions in mobile library information acceptance context-aware scene recognition. Through the spiral cycle of mutual adaptation, engagement, and failure among the four layers, mobile library information acceptance contexts evolve ecologically. The mobile library information acceptance scene recognition framework is shown in Figure 1 [Figure 1: see original paper].

Based on the service concept of "user-centered, scenario-driven,"mobile library information acceptance contexts are fused into different scene context sets according to user information needs expectations, information search habits, and information acceptance preferences, expressed as $C \rightarrow f_1(C) \rightarrow f_2(S) \rightarrow f_3(A)$. Here, C represents the raw mobile library information acceptance contexts, and S represents a scene where a user is located at a certain moment. The functions of each layer in the mobile library information acceptance scene recognition framework are described as follows: (1) **Physical Layer**: Mobile libraries collect raw user context data through various physical devices [17]. The physical layer design shields underlying hardware differences, improving system flexibility. (2) **Context Basic Layer**: This layer manages basic contexts uploaded from the physical layer, cleaning, filtering, and screening raw contexts before encapsulating them as context instances to achieve uniform standard format packaging. (3) **Scene Abstraction Layer**: This layer identifies scene rules and codes for users at specific times, processing and fusing contexts for different users in different scenes to adapt to scenario-based information needs. (4) **Application Layer**: This layer represents the multi-dimensional, multi-order fusion of all scenario-based service contexts in mobile libraries, providing response functions for user service requests in current scenes and predicting future scenes and their context configurations.

3.2 Scene Recognition Mechanism

The mobile library scene recognition mechanism is implemented through the following collaborative aspects: (1) **Context Acquisition**: Raw context data is collected through sensors, positioning systems, and mobile terminals [18] and processed before being provided to context providers. (2) **Context Classifica-**

tion: Information acceptance context data across different dimensions requires collection by different types of sensors before classification and clustering. (3) **Context Transmission**: Classified information acceptance contexts are transmitted via other devices. (4) **Scene Recognition**: Transmitted contexts are fused and abstracted according to scene functions, with contexts configured for scene functional requirements. (5) **Service Provision**: The mapper analyzes user information acceptance behaviors in identified scenes and configures contexts across different dimensions according to rules to provide services for user scenes [19]. Mobile library information acceptance context awareness enhances scene recognition effectiveness through continuous adaptation across these five stages. The mobile library information acceptance context-aware computing mechanism model is shown in Figure 2 [Figure 2: see original paper].

In the actual operation of the mobile library scenario-based information acceptance context-aware computing mechanism model shown in Figure 2, sensors collect raw contextual data for a user in a specific scene in real-time and perform certain preprocessing. Context providers obtain raw contextual data across different dimensions (such as location) from one or multiple sensors as needed, fusing and encapsulating them into scenario-based service context sets. The encapsulated scenario-based context sets are sent to the scene recognizer in the adapter for processing [20], with results being specific scenes. When the mapper detects scene changes, it invokes the required service providers based on the recognized scene.

4. Mobile Library Information Acceptance Scene Recognition Simulation

4.1 Scene Recognition Algorithm

Regardless of context richness, the number of mobile library scenes is limited, making scene recognition a classification problem [21]. Based on this, we employ the Discrete Hopfield Neural Network (DHNN) to recognize scenes in mobile library information acceptance context awareness. The Hopfield neural network utilizes different structural features and learning methods of hierarchical neural networks to simulate biological neural network memory mechanisms [22]. Mobile library scene recognition leverages the binary attribute of discrete Hopfield neural networks, where neuron outputs take only values of 1 and -1, reflecting whether contextual elements across different dimensions are activated or inhibited in a scene. The inhibition or activation states of different information acceptance contextual elements are adapted according to corresponding scene function adaptation rules, with the fusion process accomplishing the entire mobile library information acceptance scene recognition. Figure 3 [Figure 3: see original paper] shows the mobile library scene recognition mechanism model.

As shown in Figure 3, the input vector C={T, C_1, C_2, ···, C , ···, C } represents rating values of different users' experiential perception of scenario-based contexts across different dimensions, with a value range of [0, 100]. For binary neurons in discrete Hopfield neural networks, the calculation formula is u = W Y +C , where c is the contextual element input. Y =1 if and only if u ≥ , and Y =-1 if and only if u < . The state of a discrete Hopfield neural network is a collection of output neuron information. For a neural network with n output layers, its state at time t is an n-dimensional vector. S =[s_1(t), s_2(t), ⋯, s (t)] represents different scenes formed by different context configurations in mobile libraries. The discrete Hopfield neural network has 2^n states, forming an n×n weight coefficient matrix W, where W={w } (i=1, 2, ⋯, n and j=1, 2, ⋯, n), along with an n-dimensional threshold vector =[$_1$, $_2$, ⋯,   ] .

4.2 Scene Recognition Simulation

The Yunzhou Knowledge Service Space significantly enriches scenario-based information acceptance contexts in existing mobile libraries, laying a solid foundation for in-depth scenario-based services. To effectively measure resource contexts, technical contexts, service contexts, mobile contexts, terminal contexts, and social contexts in the Yunzhou Knowledge Service Space, we first establish measurable indicators for these different contextual dimensions and define specific contextual elements [23] as shown in Table 1 .

First, we randomly selected 40 users from the Yunzhou Knowledge Service Space, of which 25 volunteered. We then chose 20 volunteers and divided them into five groups to create five different scenes: campus, dormitory, library, classroom, and studio. They searched for resources on designated topics, created corresponding special collections, and could interact regarding task content. After the experiment, the 20 volunteers rated six contextual dimensions using a five-point Likert scale. The results are shown in Table 2 .

Each column in Table 2 represents mobile library information acceptance contexts: C_1 (resource context), C_2 (technical context), C_3 (service context), C_4 (mobile context), C_5 (social context), and C_6 (terminal context). The average scores of samples for different scene types TypeS c   (k=1, 2, 3, ⋯, 20) corresponding to different contextual dimensions [24] serve as ideal indicators for each scene, which become the adaptation points for the "context-user-scene" mapping in the Hopfield neural network. See Table 3 .

Each column in Table 3 has the same meaning as Table 1, while each row represents different scene types: $TypeS_1$, $TypeS_2$, $TypeS_3$, $TypeS_4$, $TypeS_5$. Since discrete Hopfield neural network neurons have only two states (1 and -1), scene perception indicators must be encoded when mapped to neuron states. The encoding rule is: when the value is greater than or equal to a certain grade indicator value, the corresponding neuron state (mobile library information acceptance context dimension) is 1; otherwise, it is -1. In the ideal five scene type context indicators, " " indicates a neuron state of 1, while " " indicates -1. Table 4 shows the perception and experience ratings of five other volunteers using the Yunzhou Knowledge Service Space, providing data for scene type recognition using the discrete Hopfield neural network algorithm.

Table 4 shows five scenes to be recognized, which may be of one type or different types. For effective recognition, we use MATLAB R2012a to implement the Hopfield neural network model. The simulation algorithm flow is: (1) Initialize the constructed Hopfield neural network; (2) Randomly select a neuron i (a certain context dimension) from the network; (3) Calculate the input C for neuron i; (4) Calculate the output value S for neuron i while keeping other neurons' outputs unchanged; (5) Determine if the network has reached a stable state. If stable or meeting given conditions, the process ends; otherwise, it returns to step (2) [25]. The mobile library information acceptance context scene recognition simulation results are shown in Figure 4 [Figure 4: see original paper].

The upper and lower graphs in Figure 4 represent ideal scene types and actual recognized scene types, respectively, for mobile library information acceptance. The simulation achieves 73% accuracy. Ideal scene recognition can effectively identify contextual elements of different scene types, while actual scene recognition results differ from ideal scenes due to certain errors, demonstrating the practical scene recognition effectiveness of this algorithm. The recognition algorithm in Figure 4 implements the context adaptation process shown in Figure 5 [Figure 5: see original paper].

In Figure 5, boxes represent functional configurations that scenes should have, while circles represent contextual elements across different dimensions. A value of 1 in a circle indicates that the contextual element is activated and adapted to scene functions, while -1 indicates inhibition and non-adaptation. The left figure shows rough context configuration effects where six context types are not fully adapted to scene functions. The right figure shows complete adaptation between the six context types and scene functions after discrete Hopfield neural network algorithm adaptation, which is the functional goal of mobile library information acceptance scene recognition.

4.3 Simulation Analysis

Mobile library scene recognition has both theoretical significance and strong practical value: (1) **Significance of scene recognition**. Mobile library scene recognition helps effectively associate user information acceptance expectations, information acceptance scenes, and information acceptance contexts in a three-dimensional manner, achieving seamless flow experiences for users during scene transitions [26]. (2) **Scene recognition methods**. Research shows that traditional pervasive computing methods for context awareness struggle to adapt to the diversity and heterogeneity of information acceptance context sources in the mobile library scene era. We need to abandon unsuitable context construction and reasoning methods for the scene era, enabling mobile library information acceptance context awareness to evolve theoretically while reducing scene recognition complexity and improving efficiency. (3) **Scene recognition accuracy**. This study is currently limited to theoretical research and small-sample testing, achieving 73% accuracy. While certain errors exist, they do not affect practical application. Additionally, this study only examines scene recognition from a macro perspective across resource, technical, service, social, and terminal contexts. Further refinement of these macro context dimensions could make mobile library scene recognition more scientific and reasonable. (4) **Future trends**. As mobile library scene elements become more deeply embedded, scenario-based information acceptance contexts will become richer and functions more personalized. How to further optimize mobile library scene recognition using the Hopfield neural network algorithm requires continued in-depth research and deserves industry attention.

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Author Contributions

Wang Fu: Responsible for topic selection, data collection and organization, paper writing, and revision.
Bi Qiang: Responsible for guidance on topic selection, research framework design, and content revision.
Zhang Han: Data collection and organization.

Note: Figure translations are in progress. See original paper for figures.