User-Centered Context Awareness and Analysis Techniques Postprint

Authors: Ye Jian, Zhu Zhenmin, Chen Yuanfei, He Zhe

Date: 2017-03-09T00:00:00+00:00

Abstract

User-centric task computing based on context awareness represents one of the primary objectives pursued by ubiquitous computing. However, extracting contextual features from high-dimensional, nonlinear, and coupled contextual data to enable computing systems to fulfill users' computational requirements amidst complex contextual variations constitutes both a research challenge and a focal point of investigation. This paper primarily addresses the implementation of intelligent context awareness oriented toward user-centric computational demands within complex ubiquitous computing environments. The research encompasses the establishment of distributed fuzzy inference models and parameter learning methodologies; the investigation of context feature analysis techniques based on manifold learning and cloud model approaches to achieve context feature extraction; and the construction of user preference computing models grounded in context awareness to realize user-centric ubiquitous computing paradigms.

Full Text

Preamble

Vol.8 No.5
Information Technology Letter
User-Centered Scene Perception and Analysis Technology
Ye Jian, Zhu Zhenmin, Chen Yuanfei, He Zhe

Abstract

User-centered task computing based on scene perception represents one of the fundamental goals pursued by ubiquitous computing. However, a key research challenge and focus lies in extracting scene features from high-dimensional, nonlinear, and coupled contextual data to enable computing systems to fulfill user computational requirements amidst complex scene variations. This paper primarily investigates intelligent scene perception for user-centered computing demands in complex ubiquitous computing environments. The research encompasses establishing a distributed fuzzy inference model and parameter learning methods; investigating scene feature analysis techniques based on manifold learning and cloud model methods to achieve scene feature extraction; and constructing a user preference computing model grounded in scene perception to realize a user-centered ubiquitous computing paradigm.

Keywords: context awareness, scene analysis, fuzzy inference, user preference model

1 Introduction

Ubiquitous computing environments are characterized by anytime, anywhere information access and invisible computing capabilities. Computational transparency and pervasiveness constitute the key technical features emphasized by ubiquitous computing. Consequently, ubiquitous computing is human-centered rather than computer-centered, aligning with the convergence trend between information space and physical space, and has become a vigorously developing international research focus. In dynamic ubiquitous computing environments, the precise execution of user tasks is closely related to environmental context (such as location and time) as well as user personalization information (such as preferences). Therefore, user tasks are scene-dependent, and the ultimate goal of scene perception is to provide decision support for user task computing in ubiquitous computing environments. However, reusing collected scene information to perform accurate scene analysis and judgment around the user-centric core remains a challenging problem that troubles us during ubiquitous computing technology implementation. This problem not only holds significant theoretical importance but also finds broad application prospects in mobile value-added services, smart homes, and urban comprehensive information services.

Current research projects with ubiquitous computing characteristics still define physical space features at the context (or "contextual") level, obtaining high-level context semantics through sensing contexts such as location, time, user identity, and computing capabilities. This approach has triggered the "context gap" problem [1][2], causing discrepancies between the context information provided by systems and what users actually need. On one hand, sensor accuracy and context representation methods lead to inaccurate data expression (contexts typically involve mixed numerical values and semantic concepts, with mutual influences among contexts), making it difficult for context information to fully reflect environmental characteristics. On the other hand, user requirements represent high-level abstract goals that exhibit significant mismatches with the abstraction level of contexts, inevitably creating gaps between context knowledge and user needs and affecting the correctness of interaction decisions between users and ubiquitous computing environments. Through scene abstraction, extracting scene features from high-dimensional context information, and investigating scene perception and analysis technologies based on context awareness and reasoning will provide new approaches to bridge the gap between context awareness and user needs.

2 Research Status

Ubiquitous computing technology research has attracted tremendous attention from governments and academia in many developed countries and regions, with substantial investments of human, financial, and material resources allocated to diverse research efforts. The U.S. Defense Advanced Research Projects Agency (DARPA), National Science Foundation (NSF), and National Institute of Standards and Technology (NIST) have all established extensive research programs for ubiquitous computing. DARPA simultaneously funds MIT's Oxygen Project [3], Carnegie Mellon University' s Aura Project [4], University of Illinois at Urbana-Champaign's Gaia System [5], the InfoSphere Project by Oregon Graduate Institute and Georgia Tech [6], and the University of Washington's Portolano [7]. Meanwhile, NIST has formulated detailed research plans for ubiquitous computing, coordinated by its Information Technology Laboratory responsible for coordination, standardization, and testing. The European Union also launched the Disappearing Computer initiative in 2001 [8], involving 17 ubiquitous computing projects with 2-3 year durations, along with related efforts like the Smart Tea/MyTea Project [9]. The UK invested €10 million to establish the six-year Equator Research Program [10].

In ubiquitous computing research projects, intelligent perception technology remains a core focus. Although context-aware systems can obtain vast amounts of data from sensor networks at any moment, this unprocessed information merely describes a single environmental attribute at a single time point, while sensor data also exhibits uncertainty and unreliability [11], making it difficult to directly obtain required semantic information. Therefore, context reasoning must be employed to extract semantic knowledge from this raw information and perform reasoning according to certain rules to obtain high-level contexts. The reasoning technologies adopted by context-aware systems draw from artificial intelligence achievements, treating context as a form of knowledge for inference. Currently, two primary approaches are employed: rule-based logical reasoning and machine learning-based reasoning.

2.1 Rule-Based Logical Reasoning

Rules typically adopt first-order predicate logic, establishing implication relationships between conditions and conclusions through rule condition definitions. Since rule logic aligns with human cognitive habits regarding the objective world, it represents a simple, practical, and commonly used context reasoning method. The Gaia system developed by the University of Illinois at Urbana-Champaign [5,12] investigates a context model based on first-order predicate calculus. This model can fully utilize Boolean expression calculus rules while incorporating quantitative processing of context information to achieve automated deduction and derivation of contexts. Bomsdorf [13] defines methods for selecting learning materials in specific contexts through rules. Policy-based calculation represents another manifestation of rule logic. Shankar [14] investigates a policy-based management framework for ubiquitous computing systems, extending ECA rules defined by policies to ECPAP rules with conflict detection to express what management actions should be executed when specific conditions occur.

The aforementioned research employs precise rule definitions. Since rules depend on empirical values, precise rules exhibit poor adaptive capabilities and cannot flexibly simulate human intelligent reasoning decision-making habits. To address this, Yu et al. [15] propose a fuzzy inference and learning method that combines fuzzy logic with inference rules to achieve fuzzification of conditional propositions and conclusions in rules, thereby completing the fuzzy inference process.

With the development of semantic Web technologies and the maturation of related theories, ontology theory has been gradually introduced into context modeling and reasoning. Ontology-based context reasoning generally employs defined inference rules, using the Resource Description Framework (RDF) to describe metadata data models, with XML, OWL, and DAML+OIL statements for modeling, and description logic or rules for reasoning. This approach can extend relational logic definitions for metadata semantics and has gradually become the representation standard for context data and high-level semantics. The Gaia system combines ontology with ubiquitous computing, using the semantic description language DAML+OIL to define context ontologies and establish interoperability mechanisms across different ubiquitous computing environments. Gaia system experiments have demonstrated the important role of ontology in context reasoning [16]. The Context Broker Architecture (CoBrA) [17] adopts OWL as the modeling tool for the COBRA-ONT ontology, using OWL' s built-in rules to detect conflicts in contexts, and processes conflicting context statements based on the hypothesis weights of intelligent agents when conflicts occur. Khedr et al. [18] implement context description creation and modification through establishing negotiation mechanisms, and build fuzzy inference rules in the reasoning engine to enable natural extension of context ontologies.

Introducing ontology into context reasoning technology provides a convenient and feasible context data modeling approach. More importantly, the combination of ontology and rule definition can discover implicit semantic relationships contained among contexts, which has been proven in many systems and models. However, rule-based reasoning approaches cannot escape dependence on experience and common sense. Whether rule definition or semantic modeling, they typically adopt offline definition methods that cannot be dynamically adjusted during runtime.

Machine learning represents a crucial characteristic of intelligent systems, facilitating research on how to adapt to system context changes in context reasoning, enabling systems to make consistent responses when encountering identical or similar contexts. Commonly employed machine learning methods for context reasoning include Bayesian networks, Hidden Markov Models, and other tools. The current research trend involves combining machine learning methods with ontology modeling and fuzzy logic to achieve hybrid reasoning models.

Bayesian networks have been widely applied in the context awareness domain in recent years, becoming the most important machine learning method in this field due to their suitability for handling probability distributions of information. The learning and decision-making process of Bayesian networks [19] is shown in Figure 1 [Figure 1: see original paper]. Gu et al. [20] perform probabilistic extension of context ontology models, using probability distributions to represent context uncertainty, and employ Bayesian networks as the tool for uncertainty reasoning on this basis. They investigate algorithms for transforming RDF graphs into Bayesian networks, which essentially involves solving conditional dependencies among metadata in metadata relationship descriptions to characterize the confidence degree of semantic relationships. Yu et al. [21] investigate a personalized hybrid multimedia recommendation system based on context awareness, proposing a recommendation model based on rules and Bayesian classifiers that uses a Naive Bayesian classifier to evaluate resources to be recommended under specific contextual conditions. Ranganathan et al. [11] investigate a hybrid learning model combining fuzzy logic rules and Bayesian networks, where context metadata is modeled using ontologies, and semantic dependency relationships among metadata are learned through fuzzy logic and Bayesian networks. Park et al. [22] propose a fuzzy Bayesian network model for context-aware music recommendation systems, applying fuzzy logic' s hybrid data processing capabilities to data preprocessing for Bayesian inference.

Hidden Markov Models represent another important machine learning method that can be used for context recognition and prediction in context reasoning, though primarily employed in wearable computing research. Clarkson et al. [23] and Starner et al. [24] apply Hidden Markov Models to location and event determination in wearable computing environments. Gopalratnam et al. [25] design and implement the Active LeZi prediction algorithm based on Hidden Markov Models and embed it in smart home environments for predicting household appliance usage.

Additionally, Support Vector Machines serve as a commonly used context classification tool. Zhang et al. [26] utilize sensors to perceive elderly people's physical characteristic parameters and employ SVM methods to determine whether the elderly person has fallen. Bulling et al. [27] use SVM to abstract eye gaze into 90 features for recognizing user states and behaviors through eye movement characteristics, achieving high recognition accuracy.

2.3 Context Reasoning Modeling Based on Petri Nets

Research on intelligent reasoning mechanisms based on Petri nets has a long history. As early as the late 1980s, Looney et al. [28] proposed approximate reasoning solutions based on Petri nets to address fuzzy reasoning requirements in the objective world, then known as fuzzy Petri nets or fuzzy logic nets. Chen et al. [29] clarified the concept of fuzzy Petri nets, proposing rule generation methods and inference algorithms for application in general knowledge representation systems. Gao [30] in 2003 proposed the definition of the Fuzzy Reasoning Petri Net (FRPN) model and designed and implemented forward reasoning algorithms based on FRPN.

Throughout research on reasoning mechanisms based on Petri nets, the focus lies on inference algorithm research. According to logical sequence, inference algorithms are divided into forward reasoning and backward reasoning approaches.

In forward reasoning [29-31], the membership degree distribution of fuzzy sets is characterized by initially enabled places in Petri nets. The reasoning objective is to obtain the membership degree of propositions represented by other places in the Petri net through initially enabled places, where membership degree reflects the truth degree of propositions. The forward reasoning model transfers membership degrees according to the transition direction defined by Petri nets, and after calculating the membership degree of a certain place, it will not re-examine the predecessor places of that place.

Backward reasoning [32] starts from the place representing the proposition to be solved, determines the reasoning tree relied upon for place solving through backtracking, and then forwardly solves the membership degrees of various places in that reasoning tree. Although backward reasoning is logically inverse to the reasoning sequence, it can eliminate the additional overhead introduced by forward reasoning for solving membership degrees of irrelevant places when calculating conclusion place membership degrees through reasoning tree construction. Therefore, backward reasoning exhibits higher computational efficiency.

2.4 Multi-Dimensional Multi-Objective Preference Model

Traditional user preference computing is mostly based on a single User Profile. From an input-output perspective, traditional preference computing models can be considered as having two-dimensional input (user preferences and recommended resources) and one-dimensional output (user ratings of resources). Higher ratings indicate higher recommendation likelihood. The formal representation of traditional preference computing models is as follows.

Let the user set be $user\_set$ and the resource set be $resource\_set$. User preferences are then defined through user ratings $R_{u,i}$ of resources. Let the rating set be $rating\_set$, then $R_{u,i}$ is defined as:

$$R_{u,i} : user\_set \times resource\_set \rightarrow rating\_set$$

Preference computing in ubiquitous computing environments is far more complex than traditional single User Profile-based recommendations, requiring full consideration of environmental context information and solving user preferences based on perceived contexts [33][34]. In this scenario, user preference computing must comprehensively consider physical context, logical context, user context, and other contextual information, extending from a binary preference model to a multi-dimensional preference model [35], i.e.:

$$R_{u,i} : user\_set \times resource\_set \times context \rightarrow rating\_set$$

where *context_set* represents context sets across different dimensions, which can be simplified as:

$$R_{u,i} : user\_set \times resource\_set \times context \rightarrow rating\_set$$

The context-aware user preference computing problem can then be described as: given $u \in user\_set$ and *context*, find *resource_set* such that:

$$rating(u, c) = \arg \max_{u \in user\_set, context} rating(u, c)$$

Furthermore, computational results may need to describe user interest in resources from different perspectives. For example, restaurant recommendation systems must consider diverse and personalized needs of different users, often requiring comprehensive evaluation from aspects such as environment, price, cuisine, and service quality. Consequently, user preference computing models evolve into multi-criteria models [35], i.e.:

$$R_{u,i} : user\_set \times resource\_set \times context \rightarrow rating\_set^N, n = 1, \dots, N$$

Naturally, the final evaluation system is closely related to application requirements. In practical applications, the essence of context-aware preference computing remains the user evaluation system under contextual conditions. The embedded context preference model layer defines the mapping from context space to user preference space, with the primary objective of integrating perceived context knowledge with user preference solving.

3 Challenges

Ubiquitous computing emphasizes user-centricity, where computing environment contexts are closely related to specific users, making scene perception crucial for ubiquitous computing realization. However, existing context-aware technologies in ubiquitous computing environments suffer from several problems:

1. **Lack of technology for analyzing computing environments from holistic scene features**: User requirements are determined by specific tasks within specific scenes. Therefore, accurate scene analysis and judgment form the foundation and important basis for satisfying user task requirements. Scene information is closely related to contextual semantics within scenes rather than being simple stacking of contextual data, requiring investigation of approaches to define scenes based on holistic contextual features of user computing environments.

2. **Lack of distributed context reasoning technology addressing ubiquitous computing characteristics**: Ubiquitous computing environments represent typical distributed systems. Current context-aware technologies primarily focus on reasoning objectives, investigating centralized reasoning through semantic rule definition and appropriate machine learning method selection. Existing fuzzy inference models concentrate on reasoning algorithms and cannot provide distributed reasoning specification mechanisms tailored to the system topology characteristics of ubiquitous computing environments.

3. **Lack of parameter learning mechanisms for fuzzy rules**: In fuzzy reasoning Petri net theoretical models, two important parameters are defined—proposition truth degree and rule confidence degree—representing the reliability of propositions and rules respectively. This concept is also reflected in machine learning hybrid reasoning technologies. However, like reasoning rule design, proposition truth degree and rule confidence degree currently depend on empirical values, lacking necessary learning methods for fuzzy rules themselves. Consequently, reasoning rules remain static and cannot reflect the accurate dynamics of propositions and inference rules.

In summary, the theories and methods based on context awareness for user-centered computing environments still exhibit numerous deficiencies. Therefore, developing scene perception and analysis theories and technologies based on context awareness holds important theoretical significance and practical value. Accordingly, this paper addresses the characteristics of distributed ubiquitous computing environments, investigating how to provide system knowledge that satisfies user requirements and conforms to scene characteristics, offering decision-making foundations for user task execution in application spaces. Specifically, this includes establishing distributed fuzzy inference methods and specification mechanisms with parameter learning functions; investigating complex scene semantic feature expression and scene analysis methods based on this foundation; and constructing user preference models embedded with scene features based on scene perception and analysis, providing decision-making foundations for aware computing-capable application systems in ubiquitous computing environments.

4 Current Research Work

Our research work primarily comprises two components: scene perception based on context reasoning and scene analysis. Scene perception technology specifically includes implementing distributed reasoning based on perceived context data sources and investigating distributed reasoning models; establishing reasoning rule parameter learning methods during the reasoning process; investigating mapping relationships between context semantics and scene feature values through scene analysis to establish learning methods required for scene analysis; and investigating user preference computing models embedded with scene features to construct a user-centered computing foundation in ubiquitous computing environments based on scene features integrated with user and task descriptions. Figure 2 [Figure 2: see original paper] illustrates the overall research framework.

4.1 Scene Perception Based on Context Reasoning

Ubiquitous computing environments exhibit distributed and heterogeneous characteristics, making it feasible to distribute reasoning tasks across different computing nodes within such environments. Reasoning rules in ubiquitous computing environments can be effectively decomposed into multiple independent propositions, providing the logical foundation for distributed reasoning implementation. We have conducted work in two aspects:

1. **Distributed fuzzy inference modeling**: Addressing the characteristics of rule-based context reasoning methods, we investigate distributed fuzzy reasoning Petri net models, extend attributes of places and transitions in the model, introduce new vector definitions regarding node states, and design and verify distributed fuzzy inference algorithms.

The basic definition of distributed fuzzy reasoning Petri nets is $dFRPN = (P, T, F, \alpha, \beta, \gamma, \lambda, \mu)$. Where $P = \{p_1, p_2, \cdots, p_n\}$ is a finite set of places representing propositions in reasoning rules. We define specific places in the place set to characterize the completion status of reasoning tasks on terminals or the status during reasoning task migration. $T = \{t_1, t_2, \cdots, t_m\}$ is a finite set of transitions representing reasoning processes. $T = R_T \cup M_T \cup S_T$, where R_T is the reasoning transition set, M_T is the migration transition set, and S_T is the submission transition set. $dFRPN$ introduces two temporal state variables– "load degree" and "load growth rate" –forming place load degree vector $L : P \to \alpha \times \beta$ and transition load growth rate vector $G : T \to \gamma \times \lambda$. Simultaneously, the mapping is revised to: $\alpha : P \to \mathbb{R}^+$ and $\beta : T \to \mathbb{R}^+$, i.e., attaching load degree definitions to places and load growth rate definitions to transitions. Consequently, in the inference algorithm of the $dFRPN$ model, both reasoning tree generation and final reasoning require system state calculation and analysis. Simultaneously, we solve proposition truth degree and rule confidence degree in the $dFRPN$ model to match proposition and rule hit degrees during the reasoning process.

2. **Fuzzy context reasoning parameter learning methods**: In fuzzy reasoning rule definitions, proposition truth degree and rule confidence degree represent the reliability and accuracy of semantics contained in propositions and rules, typically determined based on empirical values. When applying fuzzy reasoning rules, since proposition semantics in rule condition parts are inherently fuzzy, multiple reasoning rules often need to be applied for a single reasoning task, forming an applied reasoning rule set to derive fuzzy reasoning conclusions. We investigate reasoning parameter learning methods for two important parameters in fuzzy reasoning—proposition truth degree and rule confidence degree—based on proposition and rule hit degrees during the reasoning process. According to proposition and rule hit degrees in reasoning history, we solve proposition truth degree and rule confidence degree to align them with actual reasoning processes.

4.2 Scene Analysis Based on Intelligent Perception

Context information represents raw, unprocessed information describing a certain environmental attribute at a single time point. Computing environments are complex, closely related to context but not simply a superposition of multiple context information types. The purpose of scene analysis technology is to approach from holistic computing environment features, construct scene feature models based on fundamental context information, solve statistical patterns and fuzzy logical relationships embedded in mixed multimodal context information, achieve scene feature definition through limited scene feature values, and realize differentiation between different scenes.

Mapping from context semantics to scene features must consider both statistical and fuzzy characteristics of information in ubiquitous computing environments. The cloud model [36] can achieve mutual conversion between a qualitative concept expressed in natural language values and its quantitative representation, reflecting the overall quantitative characteristics of the qualitative concept. Therefore, cloud model feature values can serve as scene feature values, with distances between clouds representable through Euclidean spatial distance, enabling clustering analysis methods for cloud clustering to achieve scene differentiation. However, since dimensionality reduction loses partial features of high-dimensional context space, trade-offs between feature loss and dimensionality reduction target dimensions require in-depth investigation.

4.3 User Preference Computing with Embedded Scene Features

The purpose of user-centered scene perception and analysis is to achieve organic integration of scene features with user preference computing, establishing personalized computing for dynamic ubiquitous computing environments.

To this end, we investigate collaborative filtering algorithms embedded with scene features, with the technical framework shown in Figure 3 [Figure 3: see original paper]. This is because, on one hand, collaborative filtering technology represents the most successful and widely used approach in current personalized services. Collaborative filtering generates final recommendations through a target user' s nearest neighbors, first calculating correlations between users and/or items, then predicting the target user' s ratings for unrated items through neighbor user ratings for relevant items. On the other hand, current collaborative filtering technology is typically applied to static data without considering context. In highly dynamic ubiquitous computing environments, user decisions will be influenced by surrounding environmental contexts.

The collaborative filtering algorithm embedded with scene features introduces contextual scene knowledge into user ratings of resources. Neighbor scene determination no longer relies solely on user ratings of resources but instead performs dimensionality reduction and feature extraction based on original scene information composed of high-dimensional context data to obtain low-dimensional context feature representations. On this foundation, rating prediction strategies for collaborative filtering based on contextual scenes predict target user ratings for resources.

5 Conclusion

Research on user-centered scene perception and analysis technology holds important theoretical significance and application value, forming the foundation for further development of intelligent perception and transparent computing in the ubiquitous computing domain. This paper' s research content addresses the characteristics of intelligent IoT and ubiquitous network environments, establishing general methods for user-centered scene perception and analysis to provide decision-making knowledge foundations for intelligent human-computer interaction in these environments.

Future research will emphasize theoretical model investigation of scene perception while focusing on applying model algorithms to embedded prototype implementations in ubiquitous computing environments. This research will be supported by the National 863 Program Key Project "Key Technologies and Systems for Ubiquitous Computing Fundamental Software and Hardware" and the National Natural Science Foundation General Project "Research on Distributed Scene Perception and Analysis Technology for Task-Oriented Computing," striving to take an important step toward the development goal of novel computing environments with aware computing capabilities.

References

[1] Louise Barkhuus. The Context Gap - An Essential Challenge to Context-Aware Computing. Ph.D Dissertation, The IT University of Copenhagen, 2005.

[2] Barry Brown, Rebecca Rand. Building a Context Sensitive Telephone: Some Hopes and Pitfalls for Context Sensitive Computing. Computer Supported Co-

operative Work, 2004, 13(3-4):329-345.

[3] Larry Rudolph. Project Oxygen: Pervasive, Human-Centric Computing-An Initial Experience. Proceedings of CAiSE2001, Interlaken, Switzerland, in Lecture Notes in Computer Science, Springer-Verlag, 2001.

[4] João Pedro Sousa, and David Garlan. Aura: an Architectural Framework for User Mobility in Ubiquitous Computing Environments Software Architecture: System Design, Development, and Maintenance. Proceedings of the 3rd Working IEEE/IFIP Conference on Software Architecture. Kluwer Academic Publishers, 2002. pp. 29-43.

[5] Manuel Román, Christopher K. Hess, Renato Cerqueira, Anand Ranganathan, Roy H. Campbell, and Klara Nahrstedt. Gaia: A Middleware Infrastructure to Enable Active Spaces. IEEE Pervasive Computing, 2002, 74-83.

[6] Calton Pu, Karsten Schwan, Jonathan Walpole. Infosphere Project: System Support for Information Flow Applications. ACM SIGMOD Record, 2001, 30(1): 25-34.

[7] Mike Esler, Jeffrey Hightower, Tom Anderson, Gaetano Borriello. Next Century Challenges: Data-Centric Networking for Invisible Computing The Portolano_{Project} at the University of Washington. Proceedings of MOBICOM ’ 99, Seattle, Washington, 1999.

[8] Norbert Streitz, Achilles Kameas, Irene Mavrommati. The Disappearing Computer -Interaction Design, System Infrastructures and Applications for Smart Environments. LNCS 4500, Springer Berlin Heidelberg, 2007.

[9] Andrew Gibson, Robert Stevens, mc schraefel, Ray Cooke, Sacha Brostoff. MyTea: Connecting the Web to Digital Science on the Desktop. Proceedings of WWW 2006, Edinburgh, UK, 2006, pp.

[10] Matthew Chalmers. Place, Media and Activity. ACM SIGGROUP Bulletin, 2001, 22(3): 38-43.

[11] Anand Ranganathan, Jalal Al-Muhtadi, Roy H. Campbell. Reasoning about Uncertain Contexts in Pervasive Computing Environments. IEEE Pervasive Computing, 2004, 3(2): 62-70.

[12] Anand Ranganathan, Roy H. Campbell. An Infrastructure for Context-Awareness Based on First Order Logic. IEEE Pervasive Ubiquitous Computing, 2003, 7(6):353-364.

[13] Birgit Bomsdorf. Adaptation of Learning Spaces: Supporting Ubiquitous Learning in Higher Distance Education. Mobile Computing and Ambient Intelligence: The Challenge of Multimedia, Dagstuhl-Seminar 05181, Saarland, 2005.

[14] Chetan Shankar, Roy Campbell. A Policy-based Management Framework for Pervasive Systems using Axiomatized Rule-Actions. Proceedings of the 2005

Fourth IEEE International Symposium on Network Computing and Applications, Cambridge, MA, 2005, pp. 255–258.

[15] Zhiwen Yu, Norman Lin, Yuichi Nakamura, etc. Fuzzy Recommendation towards QoS-Aware Pervasive Learning. Proceedings of 21st International Conference on Advanced Networking and Applications, 2007, pp. 604-610.

[16] Anand Ranganathan, Robert E. McGrath, Roy H. Campbell, M. Dennis Mickunas. Use of Ontologies in a Pervasive Computing Environment. The Knowledge Engineering Review, Cambridge University Press, 2004, 18(3):209-220.

[17] Harry Chen, Tim Finin, Anupam Joshi. An Ontology for Context-Aware Pervasive Computing Environments. Proceedings of IJCAI 03 Workshop Ontologies and Distributed Systems, IJCAI Press.

[18] Mohamed Khedr, Ahmed Karmouch. Negotiating Context Information in Context-Aware Systems. IEEE Intelligent Systems, 2004, 19(6):21–29.

[19] Chihiro Ono, Mori Kurokawa, Yoichi Motomura, Hideki Asoh. A Context-Aware Movie Preference Model Using a Bayesian Network for Recommendation and Promotion. Proceedings of the 11th international conference on User Modeling, LNAI 4511, 2007, pp. 247–257.

[20] Tao Gu, Hung Keng Pung, Da Qing Zhang. A Bayesian Approach for Dealing with Uncertain Contexts. Proceedings of the Second International Conference on Pervasive Computing, Vienna, Austria: Austrian Computer Society, 2004.

[21] Zhiwen Yu, Xingshe Zhou, Daqing Zhang, et al. Supporting Context-Aware Media Recommendations for Smart Phones. IEEE Pervasive Computing, 2006, 8(34):p68-75.

[22] Han-Saem Park, Ji-Oh Yoo, and Sung-Bae Cho. A Context-Aware Music Recommendation System Using Fuzzy Bayesian Networks with Utility Theory. Proceedings of Fuzzy Systems and Knowledge Discovery, China, 2006, pp. 970-979.

[23] Brian Clarkson, Kenji Mase, and Alex Pentland. Recognizing User' s Context from Wearable Sensors: Baseline System. Proceedings of the Fourth International Symposium, 2000, pp. 69-75.

[24] Thad Starner, Bernt Schiele, and Alex Pentland. Visual Contextual Awareness in Wearable Computing. Proceedings of the Second International Symposium on Wearable Computers, Pittsburgh, PA, USA, 1998, pp. 50-57.

[25] Karthik Gopalratnam, Diane J. Cook. Active LeZi: An Incremental Parsing Algorithm for Sequential Prediction. Proceedings of the Florida Artificial Intelligence Research Symposium, Florida, USA, 2003, pp. 38-42.

[26] Tong Zhang, Jue Wang, Liang Xu, Ping Liu. Fall Detection by Wearable

Sensor and One-Class SVM Algorithm. Lecture Notes in Control and Information Sciences, 2006.

[27] Andreas Bulling, Jamie A. Ward, Hans Gellersen, et al. Eye Movement Analysis for Activity Recognition. Ubicomp 2009.

[28] Carl G. Looney. Fuzzy Petri nets for rule-based decision making. IEEE Transactions on Systems, Man and Cybernetics, 1988, 18(1): 178-183.

[29] Shyi-Ming Chen, Jyh-Sheng Ke, Jin-Fu Chang. Knowledge Representation Using Fuzzy Petri Nets. IEEE Transactions on Knowledge Data Engineering, 1990, 2(3): 311–319.

[30] Meimei Gao, Mengchu Zhou, Xiaoguang Huang, Zhiming Wu. Fuzzy Reasoning Petri Nets. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 2003, 33(3): 314-324.

[31] Huaiqing Wang, Changjun Jiang, Shaoyi Liao. Concurrent Reasoning of Fuzzy Logical Petri Nets Based on Multi-task Schedule. IEEE Transactions on Fuzzy Systems, 2001, 9(3):444-449.

[32] Shyi-Ming Chen. Fuzzy Backward Reasoning Using Fuzzy Petri Nets. IEEE Transactions on Systems, Man and Cybernetics- Part B: Cybernetics, 2000, 30(6): 846-855.

[33] Jongyi Hong, Eui-Ho Suh, Junyoung Kim, et al. Context-aware System for Proactive Personalized Service based on Context History. Expert Systems with Applications, 2009, 36(4):pp. 7448-7457.

[34] Jason J. Jung, Hojin Lee, Kwang Sun Choi. Contextualized Recommendation Based on Reality Mining from Mobile Subscribers. Journal of Cybernectics and Systems, 2009, 40(2):pp. 160-175.

[35] Gediminas Adomavicius, Alexander Tuzhilin. Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. IEEE Transactions on Knowledge and Data Engineering, 2005, 17(6): pp. 734-749.

[36] 李德毅，杜鹢．不确定性人工智能．国防工业出版社，2005.7.

Author Biographies

Ye Jian: Senior Engineer, Pervasive Computing Research Center, Institute of Computing Technology, Chinese Academy of Sciences, jye@ict.ac.cn

Zhu Zhenmin: Deputy Director and Senior Engineer (Professor Level), Pervasive Computing Research Center, Institute of Computing Technology, Chinese Academy of Sciences

Chen Yuanfei: Assistant Researcher, Pervasive Computing Research Center, Institute of Computing Technology, Chinese Academy of Sciences

He Zhe: Engineer, Pervasive Computing Research Center, Institute of Computing Technology, Chinese Academy of Sciences

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