Research on a Mobile-aware Service Model in the Internet of Things

An Jian, Gui Xiao-lin*, Yang Jian-wei, Zhang Wen-dong, Jiang Jin-hua
Department of Computer Science and Technology, Xi'an Jiaotong University, Xi'an 710049, China;
The Key Laboratory of Computer Network in Shaanxi Province, Xi'an 710049, China;
[E-mail: an.jian.sx.0218@stu.xjtu.edu.cn]
*Corresponding author: Gui Xiaolin

Received November 6, 2012; revised January 25, 2013; revised February 4, 2013; revised March 19, 2013; revised April 10, 2013; accepted April 15, 2013; published May 31, 2013

Abstract

Collaborative awareness between persons with various smart multimedia devices is a new trend in the Internet of Things (IoT). Because of the mobility, randomness, and complexity of persons, it is difficult to achieve complete data awareness and data transmission in IoT. Therefore, research must be conducted on mobile-aware service models. In this work, we first discuss and quantify the social relationships of mobile nodes from multiple perspectives based on a summary of social characteristics. We then define various decision factors (DFs). Next, we construct a directed and weighted community by analyzing the activity patterns of mobile nodes. Finally, a mobile-aware service routing algorithm (MSRA) is proposed to determine appropriate service nodes through a trusted chain and optimal path tree. The simulation results indicate that the model has superior dynamic adaptability and service discovery efficiency compared to the existing models. The mobile-aware service model could be used to improve date acquisition techniques and the quality of mobile-aware service in the IoT.

Keywords: Internet of Things, mobile-aware service, social relationships, trusted chain, mobile-aware service routing algorithm

This work is supported by National Natural Science Foundation of China (No. 61172090, 91018011), National Science and Technology Major Projects (No. 2012ZX03002001), and Specialized Research Fund for the Doctoral Program of Higher Education (20120201110013).

http://dx.doi.org/10.3837/tiis.2013.05.012

Copyright ⓒ 2013 KSII

1. Introduction

The development of the Internet of Things (IoT) achieves a closed process that includes environment sensing, data processing, and feedback control using various sensing devices and ubiquitous networks [1]. Moreover, IoT forms a new intelligent network between things, between things and persons, and between persons themselves. Compared with existing networks, IoT, which involves additional smart devices and sensing methods, increasingly focuses on people's daily lives and working environments. It has expanded our cognitive scope with data collection and analysis in innovative ways.

Collaborative awareness between persons and various smart multimedia devices is a new trend in IoT [2] because of the widespread use of modern multimedia devices, such as mobile phones and tablet computers [3], that use embedded microsensor devices to obtain useful information. The use of such information will bring a higher level of convenience to our lives. For example, suppose that Alice and Bob are two people with smart devices who do not know each other. At some point, Alice wants to obtain some useful information (such as weather or traffic conditions) about the target area in which Bob is currently located. Our research goal is to find appropriate candidate nodes (such as Bob's device) that are willing to provide the information service and establish a trusted chain among the nodes. Then, the candidate nodes supply the desired service to Alice.

The concept of mobile-aware service was proposed in previous studies [4]. The role of people in data awareness will inevitably change IoT significantly. Service requesters and providers will be not only the consumers of data awareness but also the participants and decision makers. A network of people and their smart multimedia devices will be the main platform of IoT, which will extend to the physical world through detecting, identifying, locating, tracking, and monitoring methods. However, with the new mobile-aware nodes, the mobility, randomness, and temporal-spatial complexity of people bring challenges to data awareness and data forwarding:

- With the emergence of mobile phones, tablet computers, and other communication tools, the communication radius of mobile nodes is not constrained (compared with a wireless sensor network) [3]. Any nodes could willingly interact with each other.
- The behavior of mobile nodes is controlled by social relationships. Social relationships are the activity results of mobile nodes and reveal the inherent relationships between mobile nodes. In addition, mobile nodes have a social nature, i.e., their movements and activity patterns are not aimless and disorganized when engaged in social activities [5].
- Existing research [10, 12-14] assumed that mobile nodes could trust each other when receiving and forwarding information when in communication range. In practice, however, trust relationships will lead these nodes to respond only to familiar nodes.

In social theories [5, 6, 20], the average distance between any two nodes is generally not more than six hops. Furthermore, the small world has characteristics typical of complex networks, meaning that under certain conditions, any people can establish contact. People within the same community may have similar activity patterns and close contact. Consequently, trust relationships between individuals will be established easily. These characteristics provide the theoretical basis of our research.

The purpose of this paper is to propose a mechanism of mobile-aware services in dynamic, heterogeneous, and distributed environments. We propose such a mechanism by bridging the gap between service providers and requesters to supply various services for mobile nodes.

This topic has not been considered sufficiently in previous studies, and it requires research to be conducted in new ways. In this paper, a model of mobile-aware service based on the discussion above is explored in depth. The main contributions of this paper include the following:

- We propose a service model to guide the completion of mobile-aware service and then summarize the different decision factors (DFs) using social network theory.
- We quantify the social relationships of mobile nodes with different DFs by proposing a CDOP (Community Detection based on Optimal Path) algorithm based on a directed and weighted network. The function of the CDOP algorithm is to map the physical world to a virtual society.
- We tackle the trust problem between mobile nodes with the mobile-aware service routing algorithm (MSRA) to select appropriate candidate nodes to establish trusted chains between service providers and requesters.

As mentioned above, mobile-aware service will improve reliability and quality in context-aware computing to solve the awareness-hole problem in sparse networks. Mobile-aware service is not only the link between ubiquitous-aware networks and the smart cloud but also the core carrier in the new network environment characterized by dynamic, open gathering and mobility. This type of service allows for a new collaborative and interactive mode.

The remainder of the paper is organized as follows. Section 2 reviews the existing related studies on mobile-aware services. Section 3 presents the systematic framework of our mobile-aware service model and summarizes the service realization process. Section 4 discusses the mobile-aware service in detail. Some evaluation results and corresponding discussions are presented in Section 5. Section 6 presents the conclusions.

2. Related Work

IoT is a fusion and extension of some related concepts, such as ubiquitous computing [7], machine-to-machine (M2M) technologies [8], and cyber physical systems (CPSs) [9]. Current research on mobile-aware service in IoT includes several main aspects, which are detailed below.

2.1 Mobile-aware Service

With the help of various mobile devices deployed in the real world, mobile-aware service could allow for the real-time sensing of the physical world in different areas, such as social networks, intelligent transportation, and environmental monitoring.

Andrew et al. [10] conducted research on data-aware services of sparse sensor networks deployed over a wide area. They proposed the concept of "person-centered" with a background of urban sensing. Exploiting the randomness of people, researchers used mobile devices as carriers to design two methods of opportunity sensing and shared sensing. Corredor et al. [11] presented Knowledge-Aware and Service-Oriented Middle-ware (KASOM) for pervasive embedded networks. KASOM is a novel middle-ware approach used to combine pervasive computing with a central smart cloud. The major goal of KASOM is to offer advanced and enriched mobile services to allow everyone to connect to the Internet. Considering the problem of energy consumption for mobile phone sensing applications, the author [12] defined a minimum energy sensing scheduling problem and designed a polynomial-time algorithm to obtain optimal solutions. The results demonstrated the energy problem could be solved by using collaborative mobile phone sensing applications. Nicholas

Copyright ⓒ 2013 KSII

[3] analyzed the current situation and challenges in application systems of mobile awareness based on mobile phones and designed a structure for a mobile phone-based sensing system. In [13], the author proposed the a mobile awareness system termed the BikeNet model to share the cyclist experience. The model used various sensors embedded in a bicycle to collect data about the cyclist and provided two modes to support delay-tolerant and real-time sensing. Xu et al. [14] analyzed some privacy issues in location-based services (LBSs) and designed an incremental clique-based cloaking algorithm to defend against location-dependent attacks.

2.2 Cognitive Modeling of Mobile Nodes

In a scenario of mobile awareness, the proposed service is provided mainly by mobile nodes. Therefore, the cognitive modeling of mobile nodes is crucial to mobile-aware services. Location information and behavioral patterns are collected to analyze the social relationships between nodes using a variety of sensing devices attached to mobile nodes.

Ogatha [15] proposed a method to measure the strength of social relationships by observing e-mail interactions between different nodes. Nicholas [16] used mobile phones to collect global positioning system (GPS) information from mobile nodes to compare the similarity of these nodes by their trajectories. Li [17] designed a measuring approach based on the mobile model of Hierarchical-Graph-based Similarity Measurement (HGSM). This model measures social relationships by computing the similarity of their activities trajectories. In this framework, both horizontal and vertical dimensions are considered. The horizontal dimension represents the sequence property of people's movement trajectory, and the vertical dimension represents the hierarchy property of geographic spaces. Additionally, to account for the role of mobile phones in people's interactions, a new model called Socioscope [18] was proposed to analyze the social attribute of mobile nodes with call records. Zhang and Dantu [19] assumed that the number of call arrivals is a Poisson process and used three attributes, namely, incoming and outgoing calls and a reciprocity index, as decision-making factors to calculate the interaction frequency of mobile nodes. These researchers proposed the Affinity Model (AM) to predict the trend of social relationships by collecting call records for a given period. Newman [20, 21] proposed some effective algorithms, such as the GN model and modularity, for undirected community detection depending on different network structures. Palla et al. [22] proposed the K-clique method to find overlapping communities.

Through the above analyses, we see that complexity and uncertainty are significant challenges to mobile-aware service. Although the existing results greatly enrich our understanding of social networks, there are still some shortcomings that require further research.

- Existing research on mobile-aware service is based mainly on the limitations of communication radius, and in such studies, the interaction between mobile nodes depends on multi-hop and opportunistic routing. Without considering trust relationships, mobile nodes will interact with each other as long as they can communicate. The service works similarly to sensor networks but cannot employ mobile nodes.
- Existing research on social relationships considers only a single social attribute, such as location or phone records. Multiple decision-making factors have not been considered comprehensively.
- Existing research on service patterns mainly focuses on virtual online social networking, and the social relationships between mobile nodes have generally been considered static. Moreover, in the community construction process, social relationships at the edges of networks were always set to zero or one and the networks were regarded as undirected.

Therefore, drawing on mobile-awareness [4], trusted computing [23], and other research results, the mobile-aware model presented in this paper, which is directed at the demands of mobile-aware scenarios, will analyze the DFs affecting the social relationships of mobile nodes to construct communities in directed and weighted networks in which social relationships function as edges. After a community is detected, a trusted chain can be formed from service requesters to providers. The service model can provide a means of intelligent awareness for large-scale and diverse objectives.

3. Mobile-aware Service Model

3.1 System Framework

As shown in **Fig. 1**, mining the social relationships of mobile nodes and establishing a trusted chain is a complicated process. The concrete steps are as follows:

Step 1. Quantification of social relationships between mobile nodes. With various smart multimedia devices, we can acquire people's real-time information, such as GPS and call records. This information clearly reflects people's activity patterns and social characteristics. By extracting and analyzing the different DFs affecting individuals, the social relationships of mobile nodes can be quantified reasonably and effectively.

Step 2. Community detection. Community detection is the basis of mobile–aware service. We propose an algorithm termed CDOP to detect communities in the various networks.

Step 3. Discovery of mobile-aware service providers. The MSRA selects appropriate mobile nodes within the communities constructed by step 2.

3.2 Social Relationships Based On Multidimensional DFs

Mobile-aware service mainly depends on a trusted chain derived from social relationships aggregated through different social characteristics. Therefore, reasonable quantification of social relationships is crucial to achieve mobile-aware service. In previous studies [4], various factors affecting on social relationships were defined according to the complexity, sociality, and transitivity of mobile nodes, including the location factor, interaction factor, service evaluation factor, and feedback aggregation factor.

Of these, the location factor (L) reflects the trajectory characteristics of nodes in a given period. Analyzing trajectory characteristics is helpful for determining the frequency with which different mobile nodes reach the same sensing area in a given period. The social relationships between nodes are stronger when this frequency is higher. In addition, considering the mobility features of nodes, there are hundreds of methods besides the location factor for establishing social relations, such as calling. Consequently, by collecting the call records of mobile nodes, we define the interaction factor (I) to compute their connection frequency. The service factor (S) reflects the service requester's satisfaction with the service, as specified through an evaluation after completing the service. Similarly, we also define the feedback aggregation factor (F) to reflect the characteristic of transitivity and aggregated process of social relationships.

Copyright ⓒ 2013 KSII

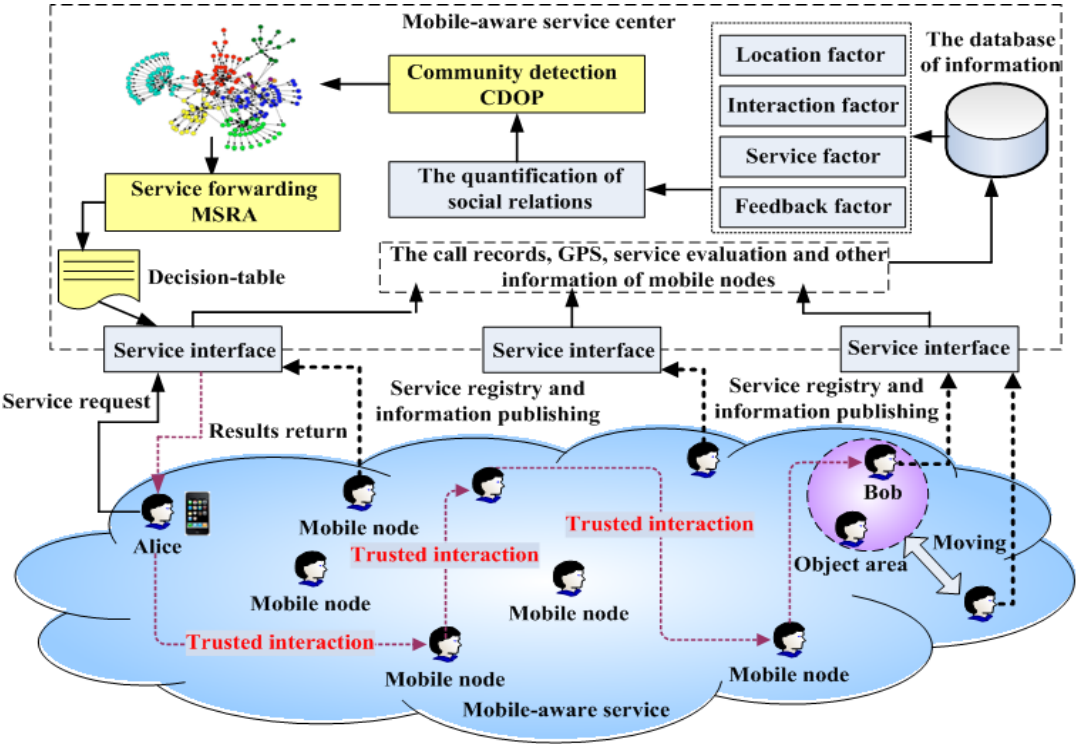


Fig. 1. Framework of the mobile-aware service model

Definition 1. The social relationship value *V(A,B)* of nodes *A* and *B* $(A, B \in N)$ is defined as

$$V(A,B) = w_1 L(A,B) + w_2 I(A,B) + w_3 S(A,B) + w_4 F(A,B)$$
$$s.t. \; 0 \le w_i \le 1, \; \sum_{i=1}^{4} w_i = 1 \tag{1}$$

where *L*, *I*, *S*, and *F* represent the different DFs and *w*1, *w*2, *w*3, and *w*4 represent the respective weights of each DF. It is assumed that nodes *A* and *B* have no social relationship if *V(A,B)*=0 and that they do otherwise.

Definition 2. The trajectory of mobile node *A* in a given period is expressed as $G = (U, ST, ET)$, where *U* is the location information of the awareness area, $U = \{l_A^1, l_A^2, \cdots, l_A^n\}$. *ST* and *ET* are the times of the node's arrival to and departure from the awareness area, respectively, where $ST = \{st_A^1, st_A^2, \cdots, st_A^n\}$ and $ET = \{et_A^1, et_A^2, \cdots, et_A^n\}$. The location factor $L(A,B)$ of nodes *A* and *B* is expressed as

$$L(A,B) = \frac{\sum_{i=1}^{n} sim(l_A^i, l_B^i)}{T} \tag{2}$$

where *T* is the time period. $sim(l_A^i, l_B^i)$ is a similarity function of the positions of nodes *A* and *B*, which reflects the encounter duration times of the various mobile nodes in the same awareness area and can be calculated through Equation 3, where α is the time threshold used to control the time interval.

$$sim(l_A^i, l_B^i) = \max\{st_A^i, st_B^i\} - \min\{et_A^i, et_B^i\} \qquad (3)$$
$$st. \left|st_A^i - st_B^i\right| \le \alpha$$

Definition 4. The service evaluation from node *A* to node *B* is recorded as $E(A,B) = \{e_{A,B}^1, e_{A,B}^2, \ldots, e_{A,B}^h\}$, where *h* is the historical record threshold of the service evaluation and $0 \le e_{A,B}^k \le 1,\ k \in [1,h]$. Thus, let the service evaluation factor *S* be

$$S(A,B) = \sum_{k=1}^{h} e_{A,B}^k \times \rho(k) / h, \quad when\ h \ne 0 \qquad (5)$$

where $\rho(k)$ is the attenuation function used to weight the quality of service and *S*(*A*, *B*)=0 when *h*=0. More recent service evaluations are given higher weight. The attenuation function is expressed as

$$\rho(k-1) = \rho(k) - 1/h,\ \ when\ 1 \le k < h \qquad (6)$$

where $\rho(k)$ =1 when *k*=*h*.

Definition 5. Assume the set of feedback values is $\{f_1, f_2, \cdots, f_n\}$ and that $V(f_k, B)$ reflects the social relationships between nodes f_k and *B*. Then the feedback aggregation factor *F* is

$$F(A,B) = \frac{\sum_{k=1}^{n} (w(f_k) \times V(f_k, B))}{\sum_{k=1}^{n} w(f_k)}, \quad when\ n > 0 \qquad (7)$$

where *n* is the number of feedback nodes. *F*(*A*, *B*)=0 when *n*=0, indicating that there are no feedback nodes in the network to provide the information. $w(f_k)$ is the weighted function expressed as

$$w(f_k) = \prod_{i=0}^{j} V(x_i, x_{succ}), \quad when\ d > 1 \qquad (8)$$

where *d* denotes the distance (hops) from the feedback node to the source node and $V(x_i, x_{succ})$ represents the social relationships from node x_i to its successor on the feedback path. In addition, $w(f_k)$ =1 when d=1.

Copyright ⓒ 2013 KSII

3.3 Community Detection

In complex networks, community detection attempts to discover a potential relationship that satisfies the following considerations. There is a relatively strong social relationship between nodes that have tight connection in the same community. However, nodes in the same community will initiate a trusted chain easily. Therefore, community is an abstraction and presentation of the social attributes of different nodes. Thus, a trust path from service requesters to service providers could be established using the community detection results.

In existing research [20-22], most network community detection algorithms can be implemented only in weighted or directed networks. However, the mobile-aware network presented here is not only weighted but also directed. To execute community detection effectively, we redefine the optimal path of mobile nodes to calculate the similarity index. In the clustering process, the quality of community division is evaluated automatically with a concept named community dispersion.

Definition 6. The optimal path from node *A* to node *B* is denoted $d(A,B)$, the maximum of all path values from node *A* to node *B* by multiplying the social relations.

$$d(A,\ B) = \max\{v(A,k) \times v(k,l) \times \cdots \times v(f,B)\} \tag{9}$$

Where *k*, *l*, *f* represent the different mobile nodes in the path from *A* to *B*.

Social relationships at the edges of a network of mobile nodes are weighted and directed. To measure the distance between mobile nodes, the optimal path of mobile nodes is proposed by definition 6. This path is the shortest distance between any two nodes. Similar to the principle of Dijskra, the definition of the optimal path is proposed as multiplying the social relationships from the source node to destination node. Furthermore, an optimal path tree is based on the calculation of the optimal path, and it is a multi-branch and multi-level tree structure.

To clarify the process of generating the optimal path tree, we assume that the network edge is undirected and that the weight is regarded as social relationships. As shown in **Fig. 2**, the detailed process of constructing the optimal path tree is as follows.

1. Take any node (such as *A*) as the root node and compute the optimal path from node A to other nodes.
2. Count one-hop-reachable nodes from node *A* according to the optimal path. For example, the optimal paths from node *A* to *B*, *C*, *D*, and *E* could be achieved within one hop. Therefore, in the optimal path tree of node A, the first layer of nodes includes *B*, *C*, *D*, and *E*.
3. Similarly, count two-hop-reachable nodes from node *A* to other nodes. For instance, nodes *F* and *J* can be reached from node *A* by two hops. Therefore, the second layer of the tree includes *F* and *J*.
4. In this manner, the optimal path tree of node *A* can be generated. It is a multi-branch and multi-level tree structure.

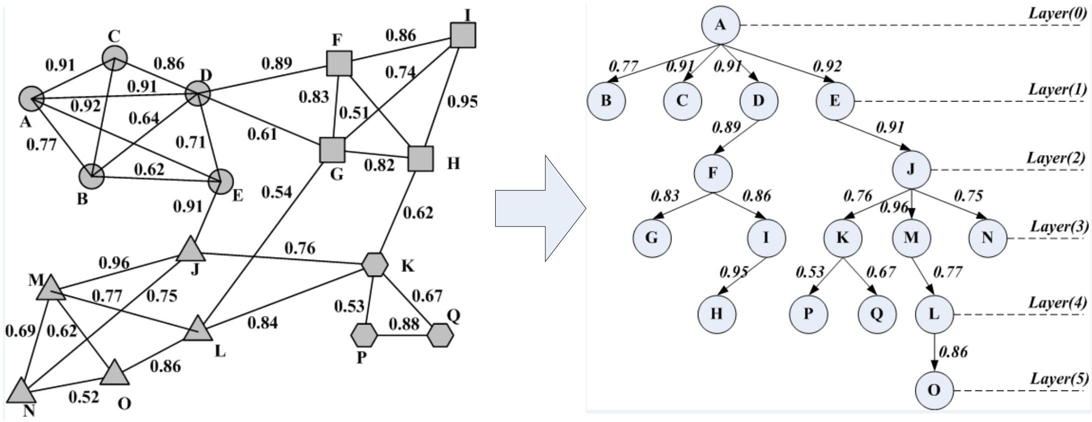


Fig. 2. Optimal path tree of mobile nodes

In social network theory, if node *A* is adjacent to node *B* in the same community, the average optimal path from node *A* to other nodes is similar to the average optimal path from node *B* to other nodes. Therefore, the similarity index (Eq. 10) between nodes *A* and *B* can be calculated to determine whether they are in the same community.

$$\Psi(A,B) = \frac{\sqrt{\sum_{k \neq A,B}^{k \in n} [d_{A,k} - d_{B,k}]^2}}{n-2} \tag{10}$$

where *n* is the number of mobile nodes and *d* is the optimal path value of different nodes. The range of $\Psi(A,B)$ is [0, 1]. The number of mobile nodes is assumed to be more than two in this paper.

Algorithm 1: CDOP

1. We can calculate the social relationships of mobile nodes according to Eqs. 1-8. Setting as the social relationship value of node *A* to node *B*, the matrix of mobile nodes can be formed as follows:

$$V = \begin{pmatrix} v_{11}, v_{12}, \cdots, v_{1n} \\ v_{21}, v_{22}, \cdots, v_{2n} \\ \vdots \quad \vdots \quad \ddots \quad \vdots \\ v_{m1}, v_{m2}, \cdots, v_{mn} \end{pmatrix}$$

2. Construct the optimal path tree of mobile nodes. As described in definition 6, we can construct a multi-branch and multi-level tree using Eq. 9. This tree is the basis of community detection.

3. Calculate the similarity index using Eq. 10. This index is used to evaluate the possibility of different nodes being in the same community, where nodes *A* and *B* are more likely to be in the same community if they have a smaller similarity index.

4. Detect a community based on the similarity index. This task contains the several steps. Firstly, initialize the subgroup denoted by Φ that includes all non-isolated nodes *i* ($i \in n$) and their adjacent nodes that have a two-way link with *i*. Secondly, test other nodes that are not in

Copyright ⓒ 2013 KSII

Φ. If there are two nodes, *j* and *k*, with $j \in (n-\Phi)$, $k \in \Phi$, and the similarity index satisfies $\Psi(j,k) \le \gamma$, where the range of γ is from zero to one, add node *j* to the community of Φ. Finally, find the next node as described above until all nodes in the network are assigned to subgroups.

5. Measure the quality of the community by defining the community dispersion *DS*. This parameter denotes the different structures between the subgroups. A larger value of *DS* indicates a more significant community structure. *DS* can be calculated as follows:

$$DS = D[F_A, F_B, \cdots, F_M] \tag{11}$$

where *A*, *B*, and *M* represent different subgroups. *D* is the variation, and represents the average optimal path of node k to other nodes. F_i represents the variation of the average optimal path in the internal subgroup. For example, subgroup *A* could be calculated as follows:

$$\begin{gathered} F_A = D[\overline{d_k}, \overline{d_l}, \cdots, \overline{d}_m] \\ \overline{d_k} = \frac{\sum_{j \neq k}^{j \in N} d(k, j)}{n-1} \end{gathered} \tag{12}$$

where *N* is the total number of nodes in the networ,k *k*, *l*, and *m* are different nodes in the community, *D* is the variation, and $\overline{d_k}$ represents the average optimal path from node *k* to other nodes.

6. Output the division result. Take the community structure for which DS is the largest as the result.

7. End.

According to Eq. 10, γ ranges from zero to one. In the proposed CDOP algorithm, different values of γ will yield different community structures. To find the optimal network structure, we also defined the parameter *DS* to measure the quality of community division. Thus, the final value of γ should result in the maximum *DS*.

3.4 MSRA

As mentioned above, the completion of mobile-aware service depends on a trusted chain. Therefore, we propose the MSRA to discover the appropriate candidate nodes in the target regions. The algorithm is based on social relationships and community structure. For example, Alice wants to acquire some useful information about the target area. First, a Service Node Set (*SNS*) is constructed by analyzing the activity patterns of mobile nodes. The *SNS* can be divided into two categories: the set of nodes in current target region when the service request is submitted and the set of nodes that may move to target region within a time threshold. Secondly, the Forwarding Node Set (*FNS*) can be constructed according to the optimal path tree of mobile nodes. If some nodes cannot provide service, we will select appropriate candidate nodes with the community-constructed CDOP algorithm. Finally, a trusted chain can be formed, and requests can be forwarded from service requesters to providers.

Algorithm 2: MSRA

1. Submit the service request (A, t, l_i), where *t* is the time label and l_i is the location information.

2. Analyze activity patterns according to Eq. 12 and select candidate nodes to form the *SNS*.

$$P_{t_i}(l_i) = \frac{M(l_i)}{\sum_{j \in k} M(l_j)} \tag{12}$$

where $M(l_i)$ is the total numbers of location l_i at which a node arrived in a period. $\sum_{j \in k} M(l_j)$ represents all possible locations.

3. Form the *FNS* according to the optimal tree and the community derived from the CDOP algorithm.

4. Construct the trusted chain between service initiators and providers with the *FNS*.

5. End.

4. Experimental Classification Results and Analysis

Simulation experiments were performed on our prototype system, which can be divided into a server side and mobile side. The server side is responsible for collecting real-time information uploaded by the mobile terminal, mining the social relationships between mobile nodes, detecting the community in the mobile-aware network, and realizing the establishment of a trusted chain. The mobile side uses the Android operating system to collect social information from mobile nodes automatically and to receive path information returned by server. Experimental data using MIT Reality Mining [25] recorded the movement trajectories, call records, and other information of 106 students and staff via mobile phones over a nine-month period.

To verify the consistency and stability of the proposed algorithm in a network environment, we selected 64 nodes with fixed social relationships as a test set. The purpose of this test was to facilitate horizontal comparison.

(a) Mobile side (b) Community detection

Fig. 3. Prototype system interface

Copyright ⓒ 2013 KSII

There were three main purposes of the experiment: (1) an internal structure analysis of a mobile-aware network, which refers to investigating the impact of our service model on the quantification of social relationships and community detection; (2) the validity analysis of the model, which attempts to detect the difference between the proposed cognitive model and other existing models in the improvement of service success rate and optimization of network distance; and (3) the dynamic adaptability analysis of the model, which examines whether the service model can provide reliable awareness services in a dynamic and uncertain environment. For reference, the results are compared to those obtained via HGSM [17] and AM [19]. The experimental parameters are shown in **Table 1**.

Table 1. Experimental parameters

Parameter	Value	Description
N	64	Number of mobile nodes
T	200 days	Time period
α	600 s	Distance similarity threshold
h	7	Service records
γ	0.017	Similarity index threshold
Call logs	2,000	Call logs

4.1 Analysis of The Network Structure

The mobile-aware network is a complex network composed of nodes and social relations. Therefore, the network overall density (*NOD*), degree center potential (*DCP*), betweenness center potential (*BCP*), external index of the network (*EI*), and the number of communities (*CN*) are defined to illustrate the evolution of the service model [26]. In addition, to ensure that the following formula is correct, the number of mobile nodes is assumed to be greater than two.

The *NOD* reflects the tightness of mobile nodes in the network. A higher *NOD* indicates that a larger number of relationships exist in the network. Let the number of network nodes be *n* and the total number of relationships between them be *m*; then, the *NOD* can be calculated as

$$NOD = \frac{m}{n(n-1)} \tag{13}$$

Mobile nodes that have more social relationships may be in advantageous positions, as they are able to control more network resources. These nodes are often decision makers in the interaction process and are able to benefit from this brokerage [27]. Therefore, the intermediate degree of relative degree (C_{RD}) is defined to represent relative centrality in network. Furthermore, to measure the power of mobile nodes, *DCP* is defined to reflect the centrality of the entire network. If a mobile node associates with many other nodes, it has more "rights". Therefore, a higher *DCP* denotes a more unevenly distributed network, and its robustness will be worse. The *DCP* can be calculated as

$$DCP = \frac{\sum_{i=1}^{n}(C_{RD\max} - C_{RD}(i))}{n-2}$$
$$C_{RD}(i) = \frac{d_{out}(i) + d_{in}(i)}{2n-2} \tag{14}$$

where i denotes mobile nodes, $C_{RD}(i)$ is the intermediate degree of the relative degree, $C_{RD\max}$ is the maximum of $C_{RD}(i)$, and $d_{in}(i)$ and $d_{out}(i)$ are the out- and in-degree, respectively.

When a node is contained in many optimal paths, the node has a greater impact on mobile-aware service. For example, if a service initiator wants to establish a connection with a service provider, he would go through other intermediate nodes. We refer to these intermediate nodes as gatekeepers. Because of high "betweenness", they control more resources in the optimal path. We calculate nodes' relative betweenness (F_{RB}) to reflect their centrality. We further calculate the *BCP* to measure the betweenness of the entire network, or the degree of control of resources.

$$BCP = \frac{\sum_{i=1}^{n}(F_{RB\max} - F_{RB}(i))}{n-2}$$
$$F_{RB}(i) = \frac{2\left(\sum_{j}^{n}\sum_{k}^{n} g_{jk}(i)\right)}{n^2 - 3n + 2} \tag{15}$$

where $F_{RB}(i)$ is the relative betweenness of mobile nodes and $g_{jk}(i)$ is the number of occurrences of node i in the optimal path between nodes j and k. $F_{RB\max}$ is the value of the maximum $F_{RB}(i)$.

We also calculate the *EI* from the numbers of external and internal relationships between subgroups in network. The *EI* measures the degree of independence between subgroups, where a higher *EI* indicates more social relationships in subgroups. The *EI* is calculated as

$$EI = \frac{IL - EL}{IL + EL} \tag{16}$$

where *IL* is the number of internal relationships within subgroups and *EL* is the number of relationships between subgroups.

Table 2. The analysis of network structure

Model	*N*	*NOD*	*DCP*	*BCP*	*EI*	*CN*
MSRA	64	0.243	0.154	0.193	0.173	7
HGSM	64	0.186	0.228	0.235	0.442	11
AM	64	0.171	0.183	0.289	0.521	13

Table 2 is obtained from an analysis of three different models with Ucinet. The

Copyright ⓒ 2013 KSII

experimental results indicate that the scope of social cognition is expanded by considering multiple factors affecting social relationships between mobile nodes. Thus, the *NOD* of the MSRA is better than that of HGSM and AM. The *DCP* and *BCP* indicate that the distribution of "right" in our model is dispersive and that the dependence between mobile nodes is lower in this model. Thus, the final network has better stability and robustness than those obtained with the other methods. The *EI* illustrates that the links between communities are closer and that the reachability between nodes is higher.

As shown in **Fig. 4**, the MIT dataset can be divided into five communities by the CDOP algorithm. Nodes of different shapes in Fig. 4 represent different communities; 37, 64, and 59 are overlapping nodes, belonging to different communities simultaneously. These overlapping nodes can be viewed as bridges between communities and are important to mobile-aware service. Nodes within the same community are closely linked; they have trust relationships with each other and can complete various service forwarding. Contacts between different communities are sparse. Therefore, the achievement of mobile-aware service depends mainly on the overlapping nodes and the border nodes between communities.

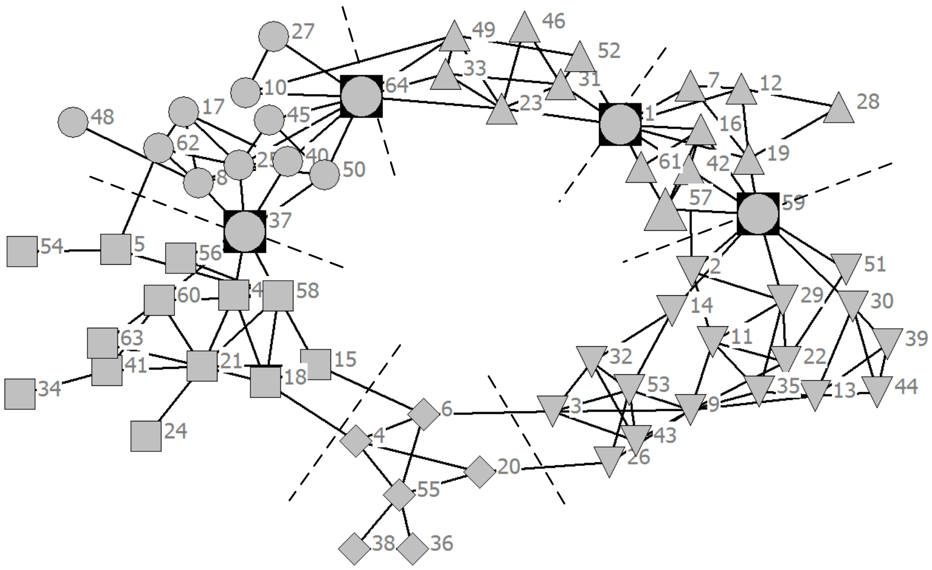


Fig. 4. Community detection

To illustrate the accuracy and effectiveness of the CDOP algorithm, we also compared it with the GN [20] and k-clique [22] methods. The standard datasets include that of MIT, a karate club [28], and a football club. The karate club recorded social networks of friendships between 34 members of a karate club at an American university in the 1970s. The football club network comes from a European football league that collected playing records of 134 teams in five countries over the last four years. There are 134 nodes and 728 links in the football club network; it can be found at http://www.uefa.com.

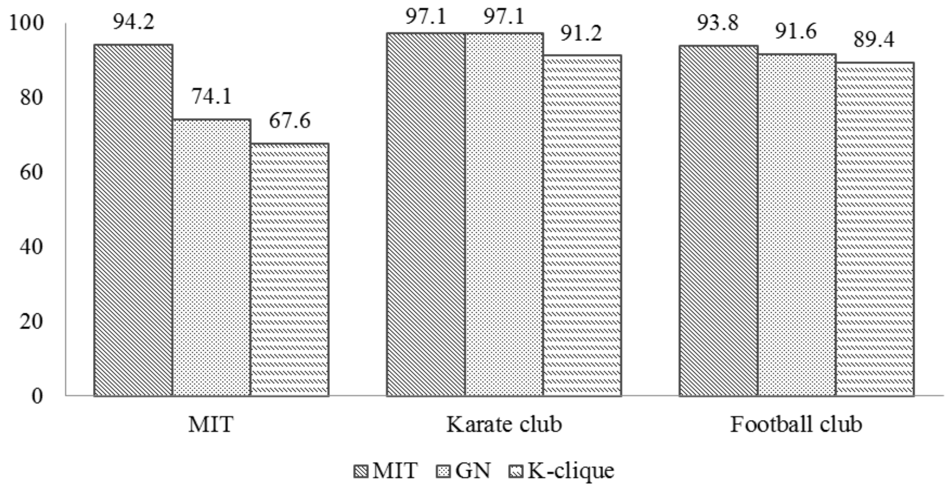


Fig. 5. Comparison of the success rate of the different methods for different datasets

In **Fig. 5**, the x-axis shows the different datasets, and the y-axis shows the success rates of the community division using the different methods. In the MIT and football club datasets, the CDOP algorithm achieves a much higher success rate than the other methods because the social network constructed by MIT is directed and weighted and the latter two methods are only suitable for undirected and zero-one networks. Moreover, in undirected networks, such as the karate club, the CDOP algorithm is also better than the K-clique method.

4.2 Validity Analysis Of The Model

The main purpose of the service model is to provide an intelligent method to improve mobile awareness within a large-scale distributed environment in IoT. Therefore, the validity analysis has two main aspects: the success search ratio (*SSR*) of services and the average distance of the service path (*ASP*).

The *SSR* is the rate at which service nodes are discovered successfully. A greater *SSR* indicates that there are more nodes in the target area that can provide mobile-aware service. The *SSR* can be calculated as

$$SSR = \frac{SN}{TN} \tag{17}$$

where *SN* is the number of successful searches and *TN* is the total number of searches.

The *ASP* measures the average number of service paths from service providers to requesters. It is calculated as

$$ASP = \frac{\sum_{i,j \in n} SP(i,j)}{n(n-1)} \tag{18}$$

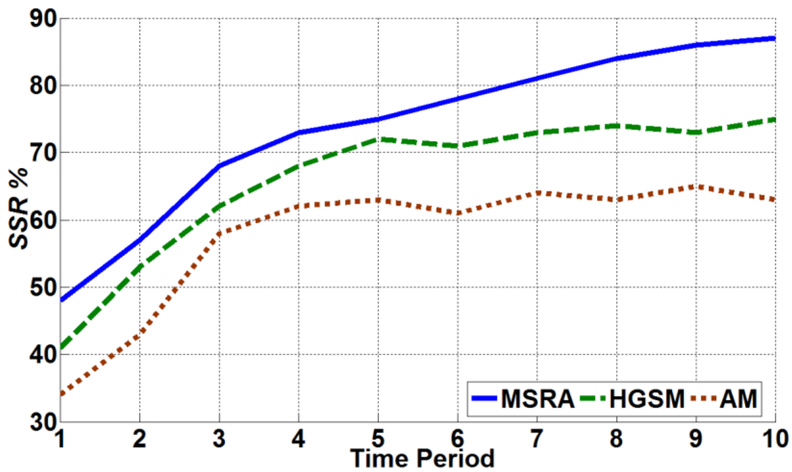
where $SP(i, j)$ is the number of social relationships from the source node to the destination node and n is the number of forwarding nodes.

The service link is calculated by social relationships, which range from zero to one. In this

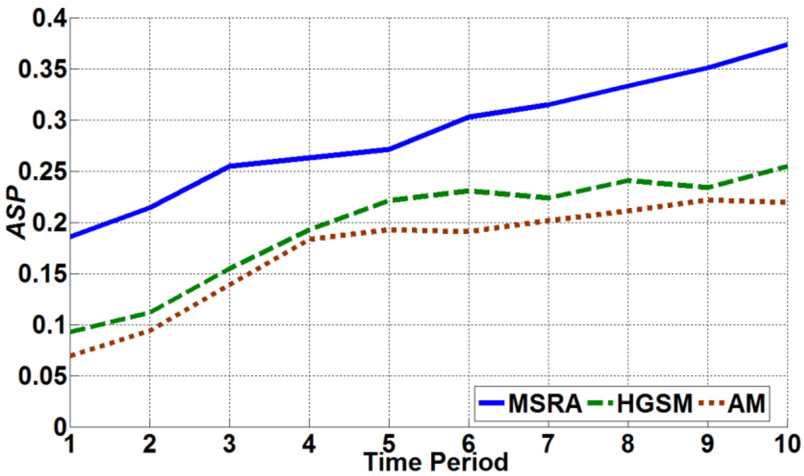
Copyright ⓒ 2013 KSII

paper, the linkage from the source node to the destination node is determined by social relationships, so a higher *ASP* denotes a stronger service link and greater likelihood of successful service.

As shown in **Fig. 6**, in the initial stage of interaction, due to minimal feedback information from mobile nodes, the network structure and social relationships are relatively fuzzy, so the *SSR* and *ASP* of the three models are not high.The indices of the three models increase significantly with increasing interaction time. However, at a later stage of interaction, the ranges of variation of the *SSR* and *ASP* in HGSM and AM are smaller. The results indicate that the internal network structure tends to be stable. For example, the *SSRs* of HGSM and AM stayed at approximately 73% and 62%, respectively. However, our model continued to grow to 87% because the cognitive model places more focus on different factors affecting the social relationships. Thus, the model effectively expands the breadth and depth of cognitive scope and has higher service efficiency in mobile-aware service, which is consistent with the above experimental analysis.



(a) SSR



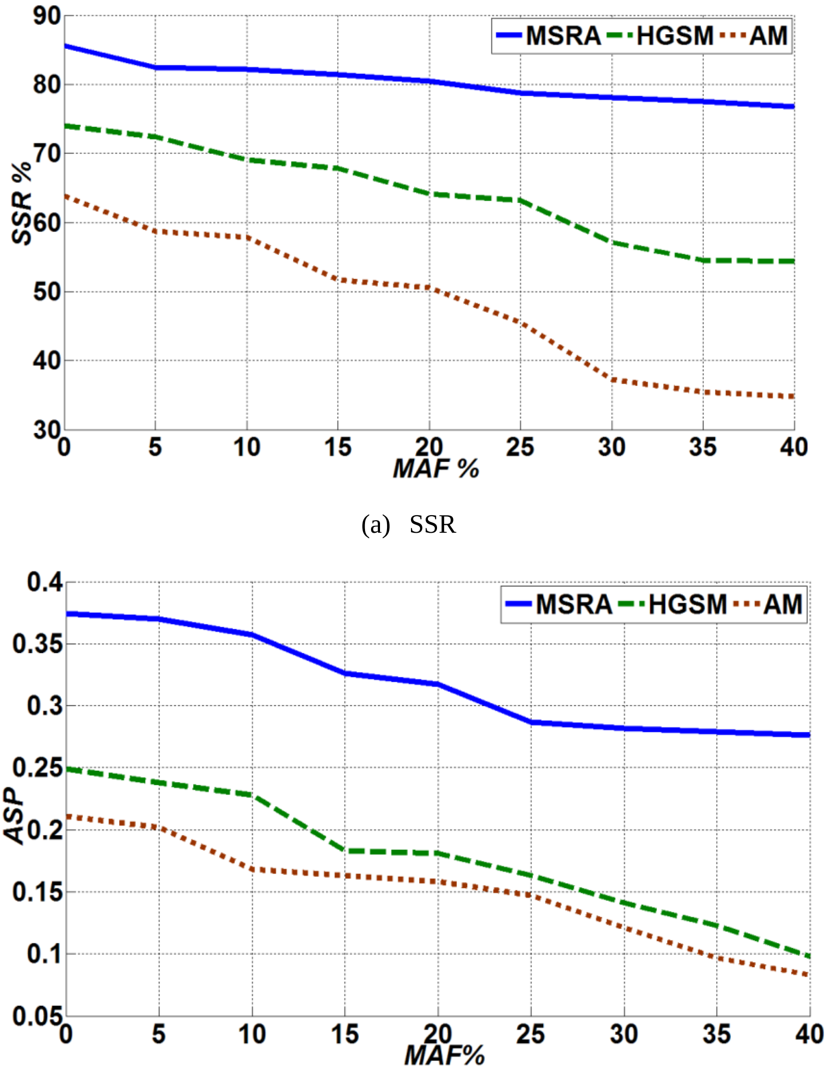
(b) ASP

Fig. 6. Validity analysis of the model

4.3 Dynamic Adaptability Analysis Of The Model

Dynamic adaptability analysis tests whether the service model can provide reliable awareness services in a dynamic and uncertain environment. Because the realization of mobile-aware services depends mainly on the mobility of nodes, the activity frequency of the mobile node (*MAF*) is defined to reflect the network dynamics. For example, when the *MAF* is 0.2, 80% of the mobile nodes in the current network provide service and 20% are unused.

Fig. 7 illustrates the simulation results under different conditions. With increasing *MAF*, the indicators of the three models suffer different degrees of decline. The average decline of *SSR* and *ASP* in our model is 7.8% and 0.083, HGSM is 14.9% and 0.11, and AM is 23.1% and 0.092, respectively. The results indicate that the model proposed here is more stable and robust and exhibits a wider distribution of social relationships. Therefore, service will not fluctuate as much when mobile nodes exit the network.



(a) SSR

(b) ASP

Fig. 7. Dynamic adaptability analysis of the model

Copyright ⓒ 2013 KSII

5. Conclusions

Various types of microsensors in smart communication devices can measure a significant amount of potentially useful information, but exploiting this information to provide services to users is rare. In this paper, a mobile-aware service model was proposed to address this problem. Using social network theory, different DFs were defined to describe the social characteristics of mobile nodes. The CDOP algorithm was then presented to detect communities in complex networks to provide a basis for decision making. Finally, the MSRA was used to build a trusted chain between service requesters and providers. Simulation results demonstrated the model has a better internal network structure than existing methods and can provide effective mobile-aware services in dynamic environments.

In future work, we plan to emphasize other aspects as follows: (1) studing service ontology and a semantic description method, (2) designing a mobile-aware service oriented around a lightweight service description mechanism, (3) studying an efficient real-time service discovery mechanism, and (4) implementing rapid service interactions between requesters and providers.

References

[1] Luigi Atzori, Antonio Iera, and Giacomo Morabito. (2010). "The Internet of Things: a survey," *Computer Networks*, vol. 54, no. 15, pp. 2787-2805, 2010. Article (CrossRef Link)

[2] Long-Xiang Gao, Ming Li, Alessio Bonti, Wan-Lei Zhou, and Shui Yu. "M-Dimension: Multi-characteristics based routing protocol in human associated delay-tolerant networks with improved performance over one dimensional classic models," *Journal of Network and Computer Applications*, vol. 35, no. 4, pp. 1285-1296, 2012. Article (CrossRef Link)

[3] D.L. Nicholas, E. Miluzzo, L. Hong, D. Peebles, T. Choudhury, and A.T. Campbell. "A survey of mobile phone sensing," *Communications Magazine*, vol. 48, no. 9, pp. 140-150, 2010. Article (CrossRef Link)

[4] Jian An, Xiao-Lin Gui, Wen-Dong Zhang, and Jin-Hua Jiang. "Social relation cognitive model of mobile nodes in the Internet of Things," *Chinese Journal of Computers*, vol. 35, no. 6, pp. 1164-1174, 2012. Article (CrossRef Link)

[5] David Lazer, Alex Pentland, Lada Adamic, Myron Gutmann, and James Fowler. "Computational social science," *Science*, vol. 323, no. 5915, pp. 721-723, 2009. Article (CrossRef Link)

[6] D.J. Watts, and S.H. Strogatz. "Collective dynamics of 'small-world' networks," *Nature*, vol. 393, no. 6684, pp. 440-442, 1998. Article (CrossRef Link)

[7] M. Satyanarayanan. "Pervasive computing: vision and challenges," *Personal Communications*, IEEE, vol. 8, no.4, pp. 10-17, 2001. Article (CrossRef Link)

[8] S.M. Babamir. "M2M architecture: can it realize ubiquitous computing in daily life," *KSII Transaction on Internet and Information Systems*, vol. 6, no. 2SI, pp. 566-579, 2012. Article (CrossRef Link)

[9] S.O. Park. "An efficient cyber physical system-based middleware for interoperability among heterogeneous devices in game environment," *Journal of Internet Technology*, vol. 12, no. 5, pp. 679-684, 2011. Article (CrossRef Link)

[10] Andrew T. Campbell, Nicholas D. Lane, Shane B. Eisenman, and Emiliano Miluzzo. "The rise of people-centric sensing," *IEEE Internet Computing*, vol. 12, no. 4, pp. 12-21, 2008. Article (CrossRef Link)

[11] Ivan Corredor, Jose F. Martinez, Miguel S. Familiar, and Lourdes Lopez. "Knowledge-aware and service-oriented middleware for deploying pervasive services," *Journal of Network and Computer Applications*, vol. 35, no. 2, pp. 562-576, 2012. Article (CrossRef Link)

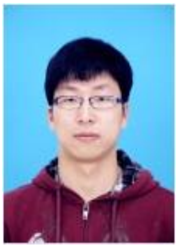
[12] Xiang Sheng, Jian Tang, and Wei-Yi Zhang. "Energy-efficient collaborative sensing with mobile phones," in *Proc. of IEEE Int. on INFOCOM*, pp. 1916-1924, May 25-30, 2012. Article (CrossRef

Link)
[13] Shane B. Eisenman, Emiliano Miluzzo, Nicholas D. Lane, Andrew T. Campbell, and Ronald A. Peterson. "BikeNet: a mobile sensing system for cyclist experience mapping," *ACM Transactions on Sensor Networks*, vol. 6, no. 61, pp.125-164. 2009. Article (CrossRef Link)
[14] Xiao Pan, Jian-Liang Xu, and Xiao-Fen Meng. "Protecting location privacy against location-dependent attacks in mobile Services," *IEEE Transactions on Knowledge and Data Engineering*, vol. 24, no. 8, pp. 1506-1519, 2012. Article (CrossRef Link)
[15] H. Ogata, Y. Yano, N. Furugori, and Q. Jin. "Computer Supported Social Networking for Augmenting Cooperation," *Computer Supported Cooperative Work*, vol. 10, no. 2, pp. 189-209, 2001. Article (CrossRef Link)
[16] D.L. Nicholas, Y. Xu, H. Lu, S. Eisenman, T. Choudhury, and A. Campbell. "Cooperative communities (CoCo): exploiting social networks for large-scale modeling of human behavior," *IEEE Pervasive Computing*, vol. 10, no. 4, pp. 45-53, 2011. Article (CrossRef Link)
[17] Quan-Nan Li, Yu Zheng, Xing Xie, Yu-Kun Chen, Wen-yu Liu, and Wei-Yi Ma. "Mining user similarity based on location history," in *Proc. of 16th Int. on Advances in geographic information systems*, pp. 34-44, November 15-17, 2008. Article (CrossRef Link)
[18] Hui-Qi Zhang, R. Dantu, and J.W. Cangussu. "Socioscope: human relationship and behavior analysis in social networks," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 141, no. 6, pp. 1122-1143, 2011. Article (CrossRef Link)
[19] Hui-Qi. Zhang, R. Dantu. "Predicting social ties in mobile phone networks," in *Proc. of IEEE Int. on Intelligence and Security Informatics*, pp. 25-30, May 16-19, 2010. Article (CrossRef Link)
[20] M. Girvan, and Mej Newman. "Finding and evaluating community structure in networks," *Physical Review E*, vol. 69, no. 2, 026113, 2006. Article (CrossRef Link)
[21] Mej. Newman. "Modularity and community structure in networks," in *Proc. of the National Academy of Sciences of the United States of America*, vol. 103, no. 23, pp. 8577-8582, 2006. Article (CrossRef Link)
[22] Palla, G., Dernyi, I. and Farkas I. "Uncovering the overlapping community structure of complex networks in nature and society," *Nature*, vol. 436, no. 7043, pp.814-818, 2005. Article (CrossRef Link)
[23] Xiao-Yong Li, and Xiao-Lin Gui. "Trust quantitative model with multiple decision factors in trusted network," *Chinese Journal of Computers*, vol. 32, no. 3, pp. 405-416, 2009. Article (CrossRef Link)
[24] M.S. Nikulin. "Hellinger distance. Encyclopedia of Mathematics," *Springe*r, 2001. Article (CrossRef Link)
[25] Nathan Eagle, Alex Pentland, and David Lazer. "Inferring friendship network structure by using mobile phone data," in *Proc. of the National Academy of Sciences*, vol. 106, no. 36, pp. 15274-15278, 2006. Article (CrossRef Link)
[26] I. Varlamis, M. Eirinaki, and M. Louta. "A study on social network metrics and their application in trust networks," in *Proc. of IEEE Int. on Advances in Social Networks Analysis and Mining*, pp. 168-175, Aug 23-25, 2010. Article (CrossRef Link)
[27] Linton C. Freeman. "Centrality in social networks: Conceptual clarification," *Social networks*, vol. 1, no. 3, pp. 215-239, 1977. Article (CrossRef Link)
[28] W. W. Zachary. "An information flow model for conflict and fission in small groups," *Journal of anthropological research*, vol. 15, no.3, pp.3452-3473, 1977. Article (CrossRef Link)

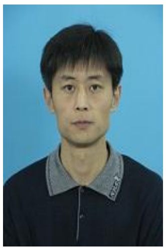
Copyright ⓒ 2013 KSII

An Jian was born in 1983. He received the B.S. and M.S. degrees in Computer Science and Technology from Xinjiang University, Urumqi, China, in 2001 and 2005, respectively. He is currently the Ph.D. candidate in Department of Computer Science and Technology from Xi'an Jiaotong University, Xi'an, China. He is also a researcher with the Key Laboratory of Computer Network in Xi'an Jiaotong University. For the last four years, their team has won the Science and Technology Progress Award of Shanxi, and a number of National Natural Science Foundation. He has authored or coauthored more than 10 articles for scientific books, journals, and conferences. In addition, his research interests also include Internet of Things, Cloud Computing and Social Computing.

Gui Xiao-lin is a professor, and he services as a Deputy Dean of School of Electronic and Information from 2013. He is also Director of the Key lab of Computer Network of Shaanxi Province, China from 2008. He leads the Center for Grid and Trusted Computing (CGTC). Professor Gui graduated with a B.S. in Computer at Xi'an Jiaotong University of China, and received M.S. and Ph.D. in Computer Science from Xi'an Jiaotong University in China in 1993 and 2001, respectively. His research interests include Network Computing, Network Security, and Wireless Networks. His recent research covers secure computation of open network systems (include Grid, P2P, Cloud); dynamic trust management theory; development on community network. He has published many leading papers in international journals and conferences. He was the recipient of New Century Excellent Talents in University of China in 2005, He has also served as program committee members for numerous international conferences, such as IEEE iThings2013, NCSC2012, ISCTSC2012, HOWAN2009, CollaborateCom2009, GCC2004.



Yang Jian-wei was born in 1989, and has received his B.S. degree in the electronic and information engineering from Harbin Institute of technology, Harbin, China, in 2012. Now, he is a M.S. degree candidate of the computer architecture engineering and also a researcher in the Key-laboratory of Computer Network in Xi'an Jiaotong University, Xi'an, China. His research interests include the Information Security and the Internet of Things.



Zhang Wen-dong was born in 1975. He received the B.S. and M.S. degree in information and engineering from Xinjiang University, Urumqi, China, in 1997 and 2003, respectively. He is currently the Ph.D. candidate in Department of Computer Science and Technology from Xi'an Jiaotong University, Xi'an, China. His research direction is embedded system, image processing and grid computing. He has authored or coauthored more than 10 articles for scientific books, journals, and conferences.

Jiang Jing-hua was born in 1988. He received the B.S. degree from the Department of Computer Science and Technology at Xi'an Jiaotong University, Xi'an, China, in 2010, respectively, where he is currently working towards the Ph.D. degree. His research interests include internet of things and social computing.