Estimating Social Tie Strength for Autonomous D2D Collaborations

Jang-Ho Choi, Dong-Oh Kang, Joon Young Jung, and Changseok Bae

***Abstract*—With the new paradigm, Internet of Things, devices are now able to share services and resources generating higher level of services. However, the management and configuration of the smart devices are often troublesome, interrupting user's primary task. To automate the process of device collaboration, smart devices should be able to configure and manage themselves, self-identifying peer devices and their relationships. Hence, we proposed the concept of device sociality, which describes social relationship between devices. In device social network with device sociality, devices are able to detect peer devices and determine resources and services to share. To derive device sociality, we investigated social relationships between users and analyzed correlations between online social interactions and social relationships. Moreover, we also investigated social ties in terms of interaction direction, individual peculiarity, and network topology. In the experiment, we not only derived directional and individualized social affinity models, but also detected organizational structure and groups of the participants, confirming the potential of D2D collaboration.**

***Index Terms*—Device social, social relationship, social network, internet of things, communication, relationship model, tie strength.**

I. Introduction

Network-equipped things are now commonplace in all fields including daily commodities. Almost all things are becoming network-capable with the new paradigm, Internet of Things (IoT), in which things are capable to generate and provide data and services. In addition to things and human interactions, things may collaborate themselves by sharing their functionalities and resources, generating even higher level of services. Since the utilization potential of IoT is almost infinite, its propagation is enormously fast, pouring out various types of products and services.

With the emerged paradigm, the users are not only geared with multiple devices, but also exposed to tremendous amount of services and resources available in their surroundings. Hence, the user often faces problems in discovering, configuring and managing the available resources. Moreover, the interaction process often incurs user interruptions and interventions. They may not only incur delays in executing task, but also degrade overall performance of the task.

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The problem shows similarity to information overflow in other fields, i.e. social networks. Although social networks provide a great infrastructure where people can make connections and exchange information, people are also exposed to unwanted connections and information. Researchers in the field proposed several methods to alleviate the problem such as collaborative filtering [1], [2] and recommender systems [3], [4].

The challenges of Social Network Services show an analogy with that of Internet of Things. In the IoT paradigm, the users are exposed to a tremendous amount of resources, which are not always useful for user's current context. Hence, in our previous research, we proposed a concept called device sociality [5] to describe social relationship between network-equipped objects. By assigning sociality to the devices, they can form a device social network, in which devices can discover trusted and necessary resources. In addition, they can authenticate and authorize discovered resources according to social affinity assigned between the resources.

Hence, in this paper, we propose social affinity models that describe social relationships and their tie strength. With social relationship and tie strength defined in device social network, devices are become capable to autonomously determine appropriate and trustable services and resources. We demonstrate experiments to show how social affinity models can be derived from online social interactions. Furthermore, we also investigate social interactions in terms of interaction direction, individual peculiarity, and network topology to confirm the potential of device sociality for autonomous D2D collaboration.

The remainder of this paper is organized as follows. Section II introduces the concept and architecture of device sociality and device social network. Section III investigates social tie and presents experiments on social affinity models to demonstrate its potential in device collaboration framework. Finally, we summarize our work and future work in Section IV.

II. Device Sociality Framework

The goal of device sociality framework is to allow devices to self-identify themselves so that they can autonomously detect necessary and trustable collaborators—whether they are human or things. In this section, we introduce the concept of device sociality and device social network for D2D collaborations.

A. Device Sociality

Device Sociality is a concept, which describes social relationship between devices. The idea is to personify

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network-capable objects—i.e. smart devices—so that they can accumulate 'social' history, acquiring various types of relationship toward other devices or human beings. Based on the acquired social relationship and its tie strength, the object can determine appropriate behaviors for received service and resource requests.

B. Device Social Network

With device sociality, the network-capable devices can form social infrastructure, which we call, *device social network*. Device social network is essentially a mimic of human social network, in which devices are able to register their profile and establish social connection with other entities, i.e. sensors and smart devices. Once the device is registered, it can detect neighboring devices. Moreover, by referring to the established social relationships, the devices are able to request/accept services and resources for device collaboration. In addition, another advantage of assigning social relationships to objects is that it can adapt existing schemes and methods of human social network with minor changes.

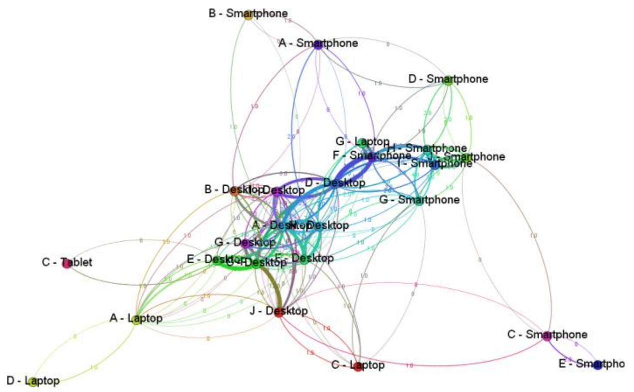

Fig. 1. An example of device social network.

We strongly believe that devices can also have various relationships toward one another similar to human beings, having different behavior for each social group. Although each device must accumulate specific social relationship towards other devices for service and resource-level collaborations, its basic social relationship can be inherited from its owner. Hence, discovering social relationship between the owners would be the primary key to assign and build device sociality.

III. Social Tie Analysis

In human social network, individuals generate new social ties to satisfy their goals [6], forming various different types of relationships: family, friends, colleagues, etc. The relationship intensity may vary depending on social interactions and emotional support between the individuals. Regarding to the relationship intensity, Mark Granovetter introduces a concept called *tie strength*—strong or weak—to describe the relationship intensity of social ties [7]. Strong ties usually refer to links between family and close friends [8], having extensive interactions [9], while weak ties refer to links between loose acquaintances [10], who often provide access to novel information.

In addition, Granovetter also proposed four tie strength dimensions namely amount of time, intimacy, intensity and reciprocal services. Later, other researchers in sociology extended the dimensions with structural factors such as network topology [11] and social factors such as race, gender and education level [12]. In this work, we focus on the primary four tie strength dimensions, mainly intensity and reciprocal services.

A. Social Affinity Models

In reality, social affinity models would be extremely complex, involving various types of social interactions. For our experiments, we simplified the model by limiting data to that are ease to collect and less reluctant to provide. We modeled social affinity as a linear combination of online interactions as follows:

$$\text{Social Affinit}\, y_{ij} = \alpha E_{ij} + \beta M_{ij} + \gamma c_{ij} + \varepsilon,$$

where

E is email interactions
M is instant message interactions
C is phone call interactions between i and j

We investigated the potential of device social network by analyzing primary social interactions among the users. In our previous work [13], we have derived personal and business affinity models in undirected form, counting all interactions between the users regardless of initiator. We analyzed a total of 397 social interactions between the users, in which we discovered email interaction was the major predictive variable for business affinity whereas instant messaging interaction was the major predictive variable for personal affinity. The results are shown in Table I.

TABLE I: Social Affinity Linear Model

(A): Personal Affinity

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	4.60419	0.53488	8.608	< 0.001
Emails	0.09982	0.05222	1.911	0.0655
Messages	0.20505	0.04064	5.046	< 0.001
Calls	1.28204	0.73167	1.752	0.09
Adj. R-squared: 0.4358		p-value: 0.0001443		

(B): Business Affinity

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	4.34931	0.62923	6.912	< 0.001
Emails	0.31288	0.06143	5.093	< 0.001
Messages	0.01672	0.04781	0.35	0.729
Calls	0.71194	0.86074	0.827	0.415
Adj. R-squared: 0.4556		p-value: 8.59e-05		

In previous investigation, we discovered several interesting facts that must be considered in social affinity modelling. First of all, we found there are leading initiators in social interactions. In fact, a large portion of social communications were one-way as the user does not always show reciprocal behaviors. Email interactions, for instance, were heavily asymmetric, as group leaders frequently send notification emails to their members. Furthermore, we also discovered that the number of interactions vary greatly depending on the user's characteristics. Some participants are more interactive, while others prefer to work alone. Lastly, we also observed that social network structure and user context also greatly influence the number of interactions. In general, there are more information flows from superior to inferior than that of vice-versa, for example. Hence, in this work, we extend our previous work, further investigating in terms of interaction direction, individual peculiarities, and network topology.

B. Directed Social Affinity Models

In this sub section, we present directed social affinity models. We transformed the collected data to directed graph, having predictive variables of outgoing/incoming emails, instant messages, and calls. The directed social interactions among the participants are presented in a graph in Fig. 2.

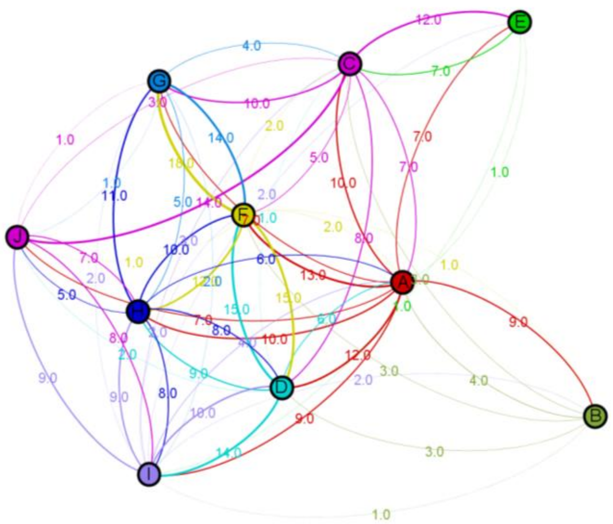

Fig. 2. Directed social interaction among participants.

TABLE II: DIRECTED SOCIAL AFFINITY LINEAR MODEL

(A): PERSONAL AFFINITY

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	2.31872	0.24127	9.61	5.77E-14
Email_out	0.05285	0.03578	1.477	0.145
Email_in	0.05517	0.03592	1.536	0.13
Message_in	0.19871	0.0361	5.505	7.24E-07
Call_in	0.68032	0.45069	1.51	0.136
Adj. *R*-squared: 0.3057		*p*-value: 1.75e-05		

(B): BUSINESS AFFINITY

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	2.22242	0.23176	9.589	4.60E-14
Email_out	0.15412	0.03809	4.046	0.000141
Email_in	0.16586	0.03809	4.354	4.83E-05
Adj. *R*-squared: 0.3814		*p*-value: 6.214e-08		

(C): AVG. AFFINITY

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	2.248	0.20491	10.971	2.41E-16
Email_out	0.10774	0.03017	3.571	0.000682
Email_in	0.11388	0.03045	3.739	0.000396
Message_in	0.10625	0.03058	3.475	0.000923
Adj. *R*-squared: 0.3372		*p*-value: 1.785e-06		

To model the social affinity, we have conducted user surveys to collect personal affinity and business affinity. The participants are members of the same research section, and they were asked to mark the two types of social affinities toward other participants. Setting the surveyed affinities as the dependent variables, we derived three types of social affinity models: personal affinity, business affinity, and combined affinity. Each social affinity is modelled as a linear combination of human social interactions, in which we observed that each affinity model has different predictive variables that are statistically significant. Hence, we applied a backward elimination technique to filter out statistically insignificant predictive variables. The modelling results are presented in Table II.

As shown in Table II, personal affinity has four variables that are statistically significant: outgoing emails, incoming emails, incoming messages, and incoming calls. Since the unit of these variables is the number of times occurred during one week, low coefficient values for incoming and outgoing emails were expected as they are the main communication channel for the participants. However, it is still valid fact that incoming calls has the highest predictive power among four variables and messages second for personal affinity. Another interesting fact in the personal affinity model is that three out of the four variables are incoming, in which we may presume the participants feel more personal fellowship toward whom they receive conversation from.

Business affinity, on the other hand, has two predictive variables that are statistically significant: incoming and outgoing emails. The result reflects the participants' work environment very well as most working communications are done via emails. Combined affinity, which is the average rating of personal and business affinity, consists of three predictive variables: incoming emails, outgoing emails, and incoming messages. While we expected the average affinity model would fit the collected data most well as many of the participants are both co-worker and friends at the same time, the business affinity model generated the highest R-squared value. From the post-interview, we discovered that a large portion of private conversations are done offline, which are not considered in social affinity modelling.

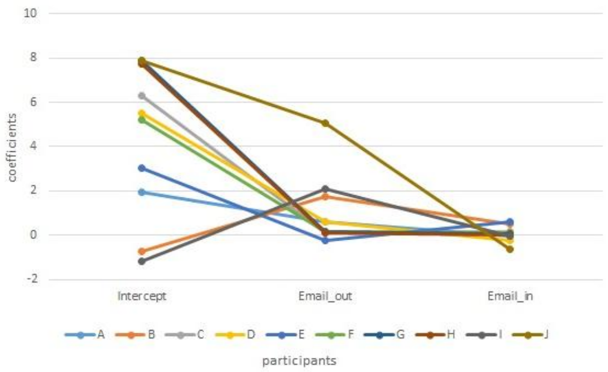

Fig. 3. Comparisons of individual social affinity models (emails).

C. Individual Coefficients

While deriving social affinity models, we confirmed that people show different behaviors and preferences while engaging in social relationships. Some people prefer instant messengers for work communication, due to its instantaneity, whereas others prefer more asynchronous communication methods such as emails because they are less interrupting.

Although the general model derived in the previous subsection can be used for cold start, individualized social affinity models are necessary for more accurate estimation. Moreover, as our device sociality framework aims for service-level collaboration. Individualized affinity models may help providing authentication and authorization in much specific and precise level. Hence, we investigated social affinity models individually, which are shown in Fig. 3.

As shown in Fig. 3, individual social affinity models show large variances in its coefficients, supporting our hypothesis. However, in reality, it would almost be impossible to generate individual social affinity models for all users. Thus, we currently consider find clusters of participants with similar behavior. On that account, in Fig. 3, one can observe groups of participants with similar coefficients: {A, E}, {C, D, F}, {B, I}, and {G, H}. Instead of modelling social affinity for every individual, we foresee to generate a social affinity model per each cluster, which may provide similar precision with significantly less effort.

D. Community Detection

Network structure is another influential factor for the social affinity model. People tend to form communities with common grounds, sharing particular information, resources, or goals together. Hence, one's social behaviors toward different communities are often dissimilar one another. For example, services one may share for family would be different from those for co-workers. Hence, groups and subgroups must be defined for appropriate authentication and authorization.

There exist a large number of community detection algorithms, many of which are originally proposed to divide computer networks for better management of network traffic. These algorithms later evolved and were applied to find groups and subgroups in social networks; and similarly, they can also be utilized in the device social network.

One of the algorithms we borrowed from the computer networks is the modularity algorithm [14]. In our experiment, we performed the modularity algorithm to find project groups among the participants. We discovered a total of four groups: {A, B}, {C, E, J}, {D, H, I}, {F, G}. These groups show a great similarity with actual project groups in the laboratory section except the fact that a few members are belong to multiple groups.

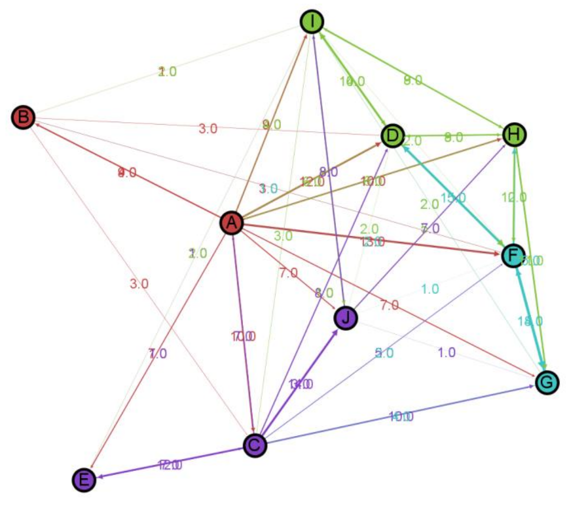

Fig. 4. Project groups detected using the modularity algorithm [14] (resolution=0.5).

The applied modularity algorithm can only detect non-overlapping clusters. In other words, each clusters have unique members, whereas in reality, people and objects can belong to multiple groups [15]. Recently, many researchers have proposed detecting uncovering algorithms such as [16]–[19], but they are often requiring large computation time and constraints.

In [20], for instance, Xie *et al*. extends Label Propagation Algorithm to find overlapping nodes and communities. The extended algorithm Speaker-listener Label Propagation Algorithm (SPA) consists of three stages: node initialization, label propagation, and post-processing stages. In the node initialization stage, each node is assigned with a unique id. Then, in the label propagation stage, a node is randomly selected as a listener, where its neighbors pass one of their labels randomly according to the predefined speaking rule. The label propagation stage is iterated until the stop condition is met. Finally, in the post-processing stage, communities can be derived from the label memory. Its time complexity is $O(Tn)$, where T is the size of label memory size. Their proposed algorithm is quite competitive as its execution time scales by nearly linear. However, its cover detection performance heavily depends on the speaking rule, which would be difficult to define in the first place.

Similar to the algorithm, we foresee to adopt the similar approaches, but with auto-generated speaking rules using explicit relationships collected from user devices and social networks.

E. Network Hierarchy

While analyzing the directed human social interaction network, we observed flows of information among the participants. A few number of nodes with high degrees have more outgoing communications than incomings, whereas the rest of the nodes have mostly incoming communications. The nodes with more incoming communications tend to have smaller degrees than that of the nodes with more outgoing communications. To observe the flows of information, we calculated the absolute difference between outgoing and incoming edges for every pair. The flows of information in the social interactions are shown in Fig. 3.

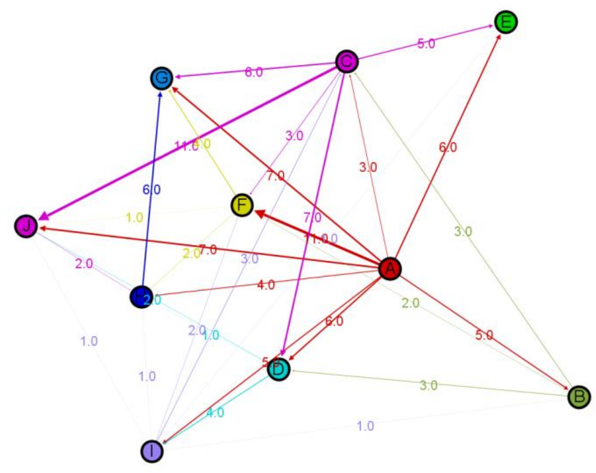

Fig. 5. Flows of information among the participants.

There is a great similarity between the flows of information and the structure of participants' organization. In the graph of Fig. 5, the node with the highest outgoing degree is A, which has edges to all other nine nodes. On the other hands, nodes with zero or almost zero outgoing degree are also detected, such as E, G, H, and J. To amplify further, we present the comparison between the flows of information and the organizational structure in Table III.

In Table III, the nodes can be divided into three groups based on their outgoing and incoming degrees. The first group has only one member, *A*, the section manager, who has mostly outgoing communications. The second group has similar number of incoming and outgoing communications, in which most of project managers fall on this category. Lastly, the third group consists of members whose edges are mostly inwards, who take parts in the project, but are not in charge of any project. The results meet the hypothesis, confirming that the organization structure can be derived by analyzing social interactions.

TABLE III: COMPARISON BETWEEN FLOWS OF INFORMATION AND ORGANIZATIONAL STRUCTURE

Id.	Out. Degree	In. Degree	Position
A	9	0	Section Manager
B	3	2	
C	5	3	Project Manager
D	3	3	Project Manager
E	0	3	
F	4	3	Project Manager
G	0	4	
H	1	5	
I	6	2	Treasure
J	1	5	

IV. CONCLUSIONS AND FUTURE WORK

This paper investigates human social relationship for autonomous D2D collaborations. To realize autonomous D2D collaboration, we proposed the concept, called device sociality which describes social relationships among network-equipped devices. In device sociality framework, devices can form device social network, where the nodes are devices and edges are device sociality. In device social network, devices can self-identify peer devices and collaborate themselves by authenticate and authorize their services and resource according to derived device sociality.

Although device sociality must be specific and accumulate their own social interactions, their primary relationships can be derived from their owners. Hence, in this paper, we investigated human social interactions and their relationships to generate social affinity models. We defined three types of social affinity models that are personal, business, and combined affinity models. We discovered that each type of affinity models holds different statistically significant predictive variables. The most influential predictive variable of personal affinity was incoming SMS, whereas emails for that of business affinity.

Furthermore, we also investigated social interactions in terms of interaction direction, individual peculiarity, and network topology. We confirmed social affinity models must be directional that participants have different social affinity towards one another. Moreover, each individual has distinct behavior while engaging social interactions, showing variances in coefficients of the predictive variables. Lastly, by analyzing social interactions, we could also successfully derive organizational structure of the participating group that leaders and managers tend to have more outgoing communications than members.

In this work, our experiment is done in closed environment. For future works, we are currently collecting more data to confirm our models are still valid in other environments. Moreover, we are extending our affinity models with additional information such as SNS, device log history such as sensors and application usages for more precise estimation. Lastly, we are investigating other dimensions of social interactions such as time and distance in social tie analysis.

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