Defining Situated Social Context for Pervasive Social Computing

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Abstract—**There is a multitude of systems in the area of mobile and pervasive social computing providing and using social context for pervasive interaction between persons. Currently, it is hard to distinguish the different approaches as there is no appropriate taxonomy available yet. In this paper we introduce the STIP taxonomy to define social context in the area of social computing and further propose to use the term *Situated Social Context* for a more focused subset of social context for pervasive social computing. We elaborate the taxonomy with a small survey of mobile social networking systems and discuss future research challenges.**

Keywords-**social networks; mobile computing; pervasive collaboration; taxonomy; survey; social context**

I. INTRODUCTION

The advent of social networking applications, and especially of websites dedicated to promoting social interaction, caused a social phenomenon in the Internet. Millions of users, some of who have little or no prior experience using online applications, regularly turn to websites such as Facebook, Twitter or Orkut, just to name a few, to keep in touch with friends, join common interest groups and publish thoughts, opinions, recommendations and up to date information about themselves. As more and more people join and use such social networking websites, virtual communities are fostered and online social interaction rises.

Meanwhile, the ever growing popularization of mobile devices with increasing features, especially smartphones, caused a comparable phenomenon in the physical world. As pervasive computing steadily becomes a reality through context-aware applications [1] which help to blur the line between the physical and the virtual worlds, people find themselves increasingly connected, even when on the move.

As both worlds are growing together with applications like Foursquare, Gowalla or Facebook Places, online social communities become pervasively accessible providing a platform for manifold interaction with network contacts both in real-time and non real-time. Thus, social computing is getting mobile or even pervasive, therefore creating a trend of **Pervasive Social Computing**.

However, in order to build social applications that benefit from mobile technologies and location-awareness, it is fundamental to understand what type of social information can be explored in a mobile environment, how it can be gathered and how it can be composed into a **Social Context** which can then be used by applications to enhance user's social experience.

The term Social Context can have many meanings or definitions, but most of them focus on the possible forms of relationships and interactions among people. Since in this paper we are specifically interested in social context that enables location-based, spontaneous interaction among people, we use the term **Situated Social Context** which we define as follows:

Situated Social Context of an individual is the set of people that share some common spatio-temporal relationship with the individual, which turn them into potential peers for information sharing or interaction in a specific situation.

This paper explores the meaning of situated social context for mobile users. Its remainder is organized as follows. Section II proposes and briefly explains dimensions of situated social context which are then applied in Section III presenting an overview of some related work. Section IV discusses some key challenges concerning situated social context. Finally, Section V presents some conclusions.

II. SOCIAL CONTEXT TAXONOMY

In order to account for the many possible meanings and definitions of Social Context [2], [3], and to clearly explain what we mean by *Situated Social Context*, we elaborated the following four-dimensional *Social Context definition space*, where each specific definition of Social Context is characterized by its spatial, temporal, inference and target people's characteristics. We call it the Social Context "STIP"-taxonomy. Of course, for most of the dimensions it would be more accurate to represent a continuum of alternatives, but for the sake of tangibility and comprehensibility we decided to stipulate only some coarse-grained alternatives/options/intervals.

Our work is not the first attempt to classify systems that combine location and social information to support new means of user interactions. In [4] the authors propose and describe a framework for classifying people-to-people-to-geographical places (P3) systems into four general categories, considering if they are synchronous or asynchronous,

people- or place-centered. The main distinctive feature of our taxonomy is that it also classifies systems according to the granularity in spatial, temporal and people dimensions, as well as their capabilities of inferring new social correlations.

S - Spatial Dimension

This dimension determines to which extent the geographical distance among the peers is relevant for the establishment of the social links and interactions.

S1: Small scope:
> This mode of social context comprehends only co-located/nearby people, i.e. people that have the potential to interact in direct, face-to-face mode within close proximity. For example this is the case for people participating in the same event like a conference or experiencing a common situation such as a car accident at some street. A small scope is also given for people being at the same place at different points in time interacting via that place.

S2: Medium scope:
> This mode encompasses people located in a same geo-political place or region. For example, all citizens of a city, region or country.

S3: Anywhere:
> In this mode, the current place/location of the peers is of no importance to establish interaction.

T - Temporal Dimension

This dimension determines the temporal aspect of the social interactions, in terms of peer discoverability and maintenance of the social links or interactions, which are directly related to the granularity of the user activity, role and group membership.

T1: Short-term activity:
> This mode includes all people that meet (or have the potential of meeting) during a short period of time (e.g., while waiting at the bus stop, by bumping into each other on the street, or being online at the same time in the same social application etc.).

T2: Mid-term activity:
> This includes individuals which may interact for some time because of their mid-term goals, for example helping each other to solve a problem at hand, e.g. finding a rare music title, installing a piece of software, fixing a flat car tire, etc.

T3: Long-term activity:
> This mode includes people that have a direct or indirect relationship due to their long-term activity, role or participation in a common project or common interest. Examples include families, fellows and friends, club members, employees, etc.

I - Inference Dimension

This dimension describes the mechanism (if any) used to infer social context. Many systems deploy some sort of detection of social correlation between individuals or groups.

I1: Decentralized:
> Social matching or inference is decentralized in a P2P way. This has the advantage that no expensive server infrastructure is needed but requires complex mechanisms to route and process information.

I2: Centralized:
> Inference is done at a central entity. Users send the information needed to infer social context to a server which processes and sends inferred social context information back to the mobile devices.

I3: None:
> No inference of social context is provided.

P - People Dimension

The people dimension represents "granularity" of people forming the social context.

P1: Individuals:
> The social context of a person consists of individual persons (i.e., friends, friends-of-friends or unknown individuals) he/she wants to interact with.
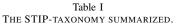
P2: Groups:
> The social context of a person consists of a group or multiple groups of people he/she wants to interact with. A group can be a cluster of friends from the social network, a group gathering at some place, or the like.

P3: Anonymous Community:
> The social context of a person consists of an anonymous community with the same social application.

The STIP-taxonomy, summarized in table I, helps us to more precisely define **Situated Social Context**. This term can be used for any system that provides and uses inferred (I1 and I2) social context to enable interaction with individuals or groups (P1 and P2), in small or medium scope regarding location of participants (S1 and S2) within short-term or mid-term activities (T1 and T2).

Dimensions	1	2	3
(S)ocial	Small scope	Medium scope	Anywhere
(T)emporal	Short-term activity	Mid-term activity	Long-term activity
(I)nference	Decentralized	Centralized	None
(P)eople	Individuals	Groups	Anonymous Community

Table I
THE STIP-TAXONOMY SUMMARIZED.

Using this definition we can further classify existing systems in the area of mobile social software along the four dimensions. As each dimension has an exclusion criteria (*3), we can also specify which of the mobile social applications actually do not provide or use situated social context but rather some more general type of social context to foster interaction between users.

III. SELECTED WORKS

To more clearly describe the usefulness of the STIP-taxonomy, we present a short survey of mobile social software ordered according to the four introduced dimensions.

A. Spatial Dimension

In this dimension, research works can be categorized into the ones that support only small scope (S1) proximity detection, the ones that focus exclusively on medium scope (S2), and some works that support both small- and medium-scope co-location detection.

In the first category, some of the most prominent systems/approaches are: SAMOA [5] is a middleware system enabling inference of previously unknown social patterns by some semantic analysis that tries to match activities/attributes of users and places profiles. The goal is to determine potential peers for social interaction based on these profiles and physical small scope co-location. MobiClique [6] is another interesting system in this category. It employs a decentralized proximity detection, where geographical and social context is associated by means of a social networking service based on a store-carry-forward content dissemination. A similar decentralized approach is also adopted by VENETA [7]. It is a mobile social network platform able to explore the social neighborhood of a user by detecting common friends of friends which are in the user's current physical proximity. This is done by Bluetooth-based proximity detection and by comparing their phone contact entries. Similarly, WhozThat [8] also uses phone proximity to exchange social network (e.g. Facebook) IDs, which are then used to fetch personal profiles from the social network.

Among the systems of the second category, S2, one should mention PeopleNet [9], which is a P2P architecture for information search in a distributed manner by propagating queries of a given type via peer-to-peer connectivity to users specific geographic locations, named bazaars. Because a bazaar can span a quite large geographical region that is determined by the set of all directly or indirectly reachable devices, PeopleNet's notion of co-loction is clearly of medium scope (S2). Another interesting work in this category is MobiSoc [10], which is able to infer previously unknown social patterns by analyzing People profiles and their mobility traces, Place profiles, and by employing People-People and People-Place Affinity Learning methods. Hence, geographical and social contexts are associated to discover new potential social ties between users. Co-location

of users is verified on the server-side, rather than employing direct proximity detection. Since the goal is to discover new social links based on the set of the user's commonly visited places, rather than particular places for a "here and now people discovery", the spatial dimension is S2. A similar spatial scope is also considered in the work on Mobile Social Ecosystems [11].

Among the analyzed works on Situated Social Context a few ones have a rather flexible definition of co-location, and thus span the S1 and S2 modes. One of them is Dodgeball [12], that was probably the first application combining LBS (Location-based Service) and Social Networks. Dodgeball's goal was to share the user's location (as a symbolic place name) in the social network and to send text messages to friends and friends-of-friends within a "distance of up to ten-blocks". Therefore, Dodgeball could be used both for small scope and medium-scope interactions, depending on the size of the coverage set by the user. The other work with a spatially-flexible approach is CenceMe [13]. CenceMe is a commercial social network for the iPhone/iPod Touch that is able to collect, classify and infer user's present status and activity from the mobile device's sensors and export this information, in real-time, into social networks. It also has a Social Context classifier running at a central backend server that computes a user's neighborhood condition, i.e. the CenceMe buddies in a user's surrounding area. Since it is aimed both at detecting new social ties based on similar visited places (like in [10]) and at identifying user proximity, it supports modes S1 and S2.

B. Temporal Dimension

Regarding the temporal dimension, many of the research systems we reviewed fall in category T1, i.e., supporting short-term activities. A typical example can be seen in PeopleTones [14], where users of the service get an alert whenever a friend or buddy is in close proximity. The goal is simply to be informed about such a "nice to know" situation and to be able to contact a person directly, enabling some kind of spontaneous interaction not possible before (e.g., to have a cup of coffee together right now). As the goal is to support spontaneous activities whenever there is time for it, the alert can be unobstrusive (e.g., by phone vibration) thus not requiring the user to look all the time at the phone, nor to be interrupted by an alert.

Most of the systems with proximity detection can be classified in S1 and T1, as proximity is most often used to involve any here and now activity which is made possible by the proximity situation. So many of the systems already introduced for the spatial dimension like MobiClique [6], SAMOA [5] and VENETA [7] fall in category T1.

FLORA [15] is an example of T1 systems beyond proximity, where users collect information for real-time collaboration. One possible application scenario is the collection of traffic updates to alert users entering a region with a traffic

jam. Further scenarios include measuring people density at public places, tracking lost people, or public transport support, e.g., letting the bus driver know that a potential passenger is waiting close to a particular bus stop.

As the distinction between categories T1 and T2 is not too sharp, we only found some systems supporting mid-term activities as their main focus (T2). Matching of requests and offers within a region, like in PeopleNet [9], is a typical example of T2 functionality as this is a mid-term activity, with a typical time frame of some days or weeks. One user may want to sell his used car, while another user is looking for a car with somehow matching preferences regarding make, price, age and mileage. Other examples for T2 are the framework for Mobile Social Ecosystems [11] and MOSS [16].

C. Inference Dimension

The inference dimension is, perhaps, the one which had the most systems we analysed fall under the exclusion criteria, i.e. I3. This suggests that, despite being a useful feature to offer users a richer social experience and lower the need for explicitly provided social information, the ability to infer social context is not yet widely supported by current systems. Nevertheless, there are systems which are able to use context data to infer and recommend new social links, either using decentralized (I1) or centralized (I2) approaches.

VENETA [7] is possibly the most straightforward example in the category of decentralized approaches, I1. It relies on a P2P architecture to allow for friends-of-friends discovery by means of comparing users mobile phone contacts. When two mobile phones are within Bluetooth communication range, it compares each user's phone contacts in order to check if there is at least a common contact. In case so, it infers that the co-located users are friends of a common friend and therefore likely candidates for social interaction. FLORA [15] is another example in this category. Although it can rely on a service provider infrastructure for centralized processing, any inference is decentralized, as users provide and process information for particular places locally. In this category we should also mention MOSS [16], the design of an infrastructure for creating and maintaining highly dynamic Mobile Social Spaces. These include community-related knowledge, content, context/presence information and the user's social links that are most relevant at each moment. MOSS proposes a decentralized approach for the publishing, discovery and management of each user's content, presence and knowledge. On the server side, however, is the knowledge warehouse that runs community building tools, with the associated user policies and a central knowledge base with its associated ontology.

In the centralized category, I2, a good example is MobiSoC [10]. As previously explained in this paper, MobiSoC is a framework which is able to use profile information and mobility traces to infer previously unknown social patterns. Even though applications developed with MobiSoC are comprised of a client which runs on mobile devices and a service which runs on regular servers, it relies on a server-based architecture in order to process collected data. Moreover, SAMOA [5] can also be classified under this category. Regardless of allowing mobile devices to act as social network managers, it relies on these managers to centrally define the criteria which will allow users to join their corresponding social networks. CenceMe [13] also uses Social Classifiers on central servers to correlate the user's current activities, visited places and establish new social links.

D. People Dimension

If we look at the people dimension, clearly most of the systems we surveyed aim at individuals (P1), i.e., the social context consists of concrete persons as the target of interaction. Within P1, the largest number of systems help the user to contact people from his list of friends within a social network or phonebook. Examples are again proximity-based services, like PeopleTones [14] and SAMOA [5], or systems tracking friends' position and their social status, like Google Latitude [17] or CenceMe [13]. The latter type of systems will be only used within a smaller circle of close friends as a lot of information is shared to create a high level of social awareness.

Friendlee [18] also targets at close friends only, as it creates a list of contacts the user often communicates with by analysing his phone behavior. It thus provides a possibility to filter out the "real" friends of a mobile user's phone book.

If we extend the scope to friends and friends-of-friends (still within the P1 category), Dodgeball [12], which was previously described in this paper, was an early system enabling interaction based on proximity where location had to be shared manually. Friends and friends-of-friends got an update whenever they were close to each other. This was inferred centrally using symbolic locations (like names of restaurants) only. VENETA [7], also previously described in this paper, is an example for serverless friend-of-friend detection based on Bluetooth technology.

The last subgroup within P1 is the encounter of unknown individuals like in aka-aki [19]. Users of such applications are interested in finding new acquaintances. If two users of the system are in close proximity, they exchange profile information via Bluetooth and are thus able to check if the other person might be interesting and to contact him or her directly.

There is also a number of systems where the interaction based on situated social context is not targeting at individuals but groups of people (P2). Cluestr [20] focuses on the initial group formation process and proposes a list of contacts from the same group if the user selects a contact from his phonebook. To achieve this, the tool performs analysis on the social graph extracted from a social network like

Facebook. The interaction will then take place between the user and the group he selected, that's why we chose to place Cluestr in the P2 category. Another typical P2 example is FLORA [15], where groups of persons are built location-dependent to enable real-time collaboration between the users. We already mentioned some of the envisioned scenarios earlier in this section. An additional interesting P2 system is Socialaware [21]. It supports groups gathered at some place, e.g., to create a playlist matching the preferences of the audience near a jukebox.

IV. KEY CHALLENGES

As we have seen, most of the approaches for Pervasive Social Computing with specific support for Situated Social Context have been worked out in research projects and implemented as prototypes, and only very few have been launched as start up commercial applications or social networks (e.g. [12], [19] and [13]). In spite of the several appealing features and characteristics embodied in these current systems, it is clear also that this field still holds many challenges [22] some of which are discussed in this section.

A. Dealing with Uncertainty

Since Pervasive Social Computing heavily relies on context information derived from sensor data, which has a limited precision and accuracy, much work has to be done in the area of context classifiers and inference methods based on probability. Moreover, the users should always be aware of the kind of information that was used, which are the uncertainty involved, and which was the method used to compute the context-social correlations and issue the corresponding recommendations. And finally, the systems should also be capable of receiving feedback of the users and enhancing their methods using machine learning.

B. Lack of Standards

Existing social networking application providers, especially Internet based websites such as Facebook, Twitter or Orkut, have been able to collect massive amounts of social data thanks to their immense popularity. Although one can expect that such data is being thoroughly used in order to improve each providers services, not enough effort has been put into allowing service integration and providing a unified communication model. Despite efforts like OpenSocial [23], no widely accepted standards have been defined concerning how social data is stored and accessed. Each provider typically offers its own, proprietary, API for application development and follows different access policies. This lack of standards hampers integration between different social networking applications and the potential for mobile applications to accelerate social context exploration by taking advantage of existing Internet based social networking websites.

C. Social Data Mining

Social information is not only subjective, but also dynamic. Therefore, building a social context and keeping it up to date is not an easy task. It is possible to extract social information from a wide range of different sources: existing Internet based social networking applications where such information has already been entered by the user or by the user's friends or acquaintances, sensor data (such as location or environmental noise level) or even mobile device data (such as phonebook or last dialed numbers). However, efficient data mining techniques are needed in order to allow data from different sources to be combined, turned into something meaningful and finally used to infer social patterns that can improve users experience and allow for better social interaction features.

D. Privacy Issues

Social networking applications have raised a number of privacy issues. While users seem to agree with exposing some personal information in exchange for services, they also have reasonable privacy expectations. Meanwhile, social networking application providers struggle not to frustrate users expectations by establishing and publishing acceptable data usage policies. Nevertheless, liability issues still remain unclear as frequent disputes arise concerning data breaches and third-party unintended usage of users social information. As more users turn to social networking applications, and consequently more personal data is collected by providers, privacy issues will need to be thoroughly addressed.

E. Further Inference and Matchmaking Mechanisms

From our analysis, we have noticed that although most papers recognize the potential benefits of cross-analyzing sensed and profile data, with information about social links, actually most of the existing inference, correlation or matchmaking approaches so far are quite limited and usually focus only on detecting new potential social ties, or recommending places to visit. Thus, we feel that here there is a huge potential for the development of more powerful inference methods, where patterns of sensed information from socially connected users may be also be used to deduce the user's current activities and goals, paving the road for innovative applications of pervasive social computing.

V. CONCLUSION

In the last few years we have witnessed the explosion of the number of systems that exploit Pervasive Social Computing, and where usually the user's location plays a central role for the establishment of new social ties. Among these, an increasing number of works now specifically focus on establishing and maintaining what we named Situated Social Context, i.e. groups of people that are at the same place and time, and that are potential peers for spontaneous

and opportunistic interactions due to their social ties, current activities or profiles.

However, in order to better understand the similarities and differences among the approaches we felt the need of a taxonomy for such Social Context, and we came up with one based on a four-dimensional design space. By classifying the surveyed systems according to this taxonomy we could not only see the range of possible design alternatives, but also identify that in the inference aspect holds the biggest research challenges and opportunities for future development. In addition, other problems like lack of privacy controls and of standard interfaces become major hurdles for the integration of such systems and social networks and its widespread adoption.

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