Groupanizer: a Method to Correlate Multi-users Position with Daily Moments

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Abstract

Groupanizer is an extension of groupware and constitutes a development platform to integrate user-centric information for the benefit of groupware applications. User-centric context is used in a collaborative manner to positively link and reinforce group member idiosyncrasies. In order to do so, monitoring of the user's daily context is essential, and thus, one aspect we aim at integrating is user physical position. We believe that common visited places and trajectories constitute one user-centric element that should be used to bias transactions -- namely tasks or scheduling -- in groupware. Although physical location could by itself be integrated in a model, we believe that motion behaviors are intrinsically linked to moments of daily life. We define those moments using three context elements -- a time period, an activity and the current day. This definition leverages position mapping to include its implicit nature. Essentially, the aim is for our model to ideally reflect a group's ecology, namely relations between multiple users given their current and future locations. This paper defines the ontology, mapping locations and moments among users, and the Hidden Markov Model used to derive location patterns. Finally, it describes the experimentation phase and its results.

1. Introduction

The advent of ubiquity and mobility in computer networks has drastically influenced our views about computing platforms and virtual environments. Many efforts have focused on integrating a heterogeneous device environment to optimize the available resources to a group or a work environment through a seamless middleware layer [1,2,3]. However, in a ubiquitous environment, not only do heterogeneous devices need to be integrated, but also heterogeneous personalities, user feelings, attitudes or objectives. Thus, Groupanizer aims at reusing this heterogeneity, applying it to human behaviors. Its function is to create an ideal context among users to aid in sharing ideas, scheduling meetings or activities and in distributing tasks. In other words, Groupanizer aims at creating the ideal collaborative community context.

1.1. Ideal Collaborative Community Context

Toru Ishida has suggested that community computing includes five different heuristics for encouraging social interactions among people within a community [4]. The left column in table 1 identifies those five heuristics and the right column specifies those which this project aims to promote.

Table 1 Community computing heuristics

Heuristics	Groupanizer
Knowing each other	-----
Sharing preferences and knowledge	Yes
Generating Consensus	Yes
Supporting everyday life	Yes
Assisting social events	-----

Furthermore, the following two arguments represent complementary heuristics that depict what we believe to be motion *triggers*. More precisely, if we can determine someone's motivations or intentions, we can certainly derive a location prediction mechanism, which better reflects his reality within a community. As put forth by Wang et al. [7], groups are often formed for a specific purpose such that their collaborative interactions become predictable. Thus, we do not intend to derive motion behaviors of random individuals, but we focus on existing, loosely organized groups such as friends, a laboratory or any organization. One could make a parallel with the fictional science *psychohistory* imagined by Isaac Asimov where the analogy of a gas is used to exemplify that the motion of a single molecule is very difficult to predict, but the mass action of the gas can be predicted to a high level of accuracy [5].

1.2 Motion triggers

1. *Displacements are intrinsically linked to moments*
2. *Group motions influence an individual's motion*

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Locations are by definition linked to a purpose or an action. For instance, one moves from a resting state at home, to a working state at the office, and finally to a dining state at the restaurant for lunch. These three locations, namely home, office and restaurant, are closely linked to an action, and a period of a specific day. One can say that the nature of a current moment defines a future destination. Indeed, being at the office on a Monday might trigger a lunch event with colleagues, however, being in the same situation on a Sunday might trigger a business trip on the Monday.

The group often plays a central role in biasing motion behaviors. One group member may well do as another does. The difficulty lies in finding which set of users holds an influence on your motion behaviors. This being said, collocation patterns definitely constitute one way to include such an influential mechanism within a model. The fact that someone else shared some moment with you in a similar location almost certainly has a stronger influence on your behavior than someone with whom you do not share time or a space.

Based on these premises, the objective is to automatically derive a daily schedule or personal intentions of participants from the history of their motion behaviors within a community. As argued by Ferscha et al., location as the sole context information type is not sufficient to support group interaction [6], and the integration of other primary context types as pointed by Dey [8] is necessary. Indeed, we have defined a common ontology to map locations and moments in accordance with Dey's four generic context identifiers: *location*, *identity*, *time*, and *activity* as described in the next section.

2. A location-naming ontology

Finding a universal naming system for locations constitutes quite a challenge. Indeed, many locations have different specifications depending on their user, but it is important for a location name to make sense to everyone within the community. For instance, a referencing system must be established in order for everyone to understand their personal location as well as their location within a community context likely suggested by Toru Ishida's common ontology definition [4]. In light of this, we have established three interrelated levels of location refinements namely the Personal Location Mesh *PLM*, the Shared Location Mesh *SLM*, and the locations.

2.1 Personal Location Mesh

Upon registration at the Groupanizer web site, a user defines a personal location mesh comprising more or less five areas. Each of them solely identified by a name. These 5 areas represent reference points to map a community of salient locations. For the purpose of the experimentation each area is linked to a single SLM. One could view the registered PLM as areas respectively covered by a single cellular communication tower, or more concretely five GSM cells.

2.2 Shared Location Mesh

An important distinction has to be made between a *personal location mesh (PLM)* and a *shared location mesh (SLM)*. The PLM represents a mapping of a personal environment and the SLM describes an environment common to a group of individuals. For instance, a school or a work place often constitutes a shared environment within which a set of fixed locations can often be derived such as, a cafeteria, a library, a bookstore, classrooms and a laboratory in the case of a school environment. The purpose of an SLM is to give a zoomed perspective of an area (GSM cell). The SLM comprises an SLM descriptor, all participating users, its public availability and a title, which constitutes the *identity* context identifier of a location belonging to the underlying community. One links a *PLM* with an *SLM* through a friend's invitation or via an *SLM* query at the Groupanizer web site.

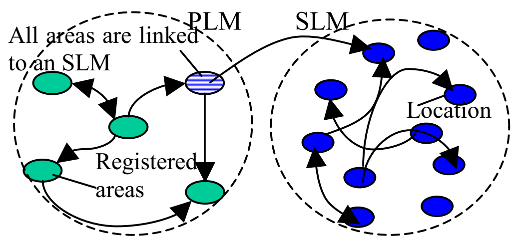

Figure 1 PLM and SLM relationship

2.3 Locations

Each SLM location is defined by a set of three parameters or attributes, namely a location name (*location*), a location purpose (*activity*), and time (*time*). These three parameters enable the system to identify moments associated with a location.

First, the name identifying the location is left to the discretion of the user. This has been demonstrated to be an effective method, since people prefer to share a symbolic link or a name with others rather than use a precise addressing system [13]. One might argue that a liberal naming system becomes contentious, since all participating community members are allowed to populate the location mesh (*SLM*). However, in a shared environment such as a university campus we assume that most of the places are tagged with specific names such as the gymnasium, the pool, the general library, or classroom 268 restricting the naming options to the most common and unique naming possibilities listed above. Also, if Ann is a co-worker of mine and she is talking about the 7/11 convenience store at work, I believe that even though there are many 7/11 in Tokyo, she is probably referring to the one close to our common work area.

The location purpose is identified by 7 keywords that represent typical daily activities such as *dining*, *sports*, *social*, *work*, *rest*, *shop*, and *commute*. Then, the time attribute specifies the time of a location's visit.

3. The prediction model

Groupanizer has as its objective to reinforce the efficiency of interpersonal communication suggesting that communications build upon a shared understanding of the past, current and last but not least future context within which interactions take place [12]. In light of this, we believe that efficient prediction of future context, in which interpersonal interactions could occur, is a key to promoting effective communication.

3.1 Groupanizer's Model

The ontology described in section 2 allows our predictive model to rely on four contextual parameters to efficiently correlate locations with daily moments as depicted by table 2. Above each parameter of our model figures between parentheses a reference to Dey's four generic context identifiers [10].

Table 2 Groupanizer information structure

GROUPANIZER MODEL DEFINITION					
(Location) **Source**	*(Activity)* **Activity**	*(Time)* **Day**	*(Time)* **Period**	*(Identity)* **SLM**	*(Location)* **Destination**
6f6	work	Tue	evening	Aml	Kashiwa

1. The **Source** identifies the source location;
2. The **Activity** is described through one of 7 keywords;
3. The **Day** is extracted from the recording timestamp;
4. The **Period** is also extracted from the recording timestamp;
5. The **SLM** is defined by any user part of a community, and made publicly available through Groupanizer web site;
6. Finally, the **Destination** identifies a possible future location, which is the final prediction objective of our model.

In order to efficiently integrate all six elements above, an HMM representation has been generated, mainly for its sequential timeline property derived from discrete Markov chains.

3.2 Representation of Observations and States

Since one HMM is created for one cluster of locations identified by an SLM, only locations part of that SLM are assigned as the states of that model. Even though, many Markov Models have been used in previous research to incorporate location prediction using, for example GPS and signal loss such as in the case of Ashbrook et al. and Marmasse et al. [11,12], or GSM cells and transitions to identify salient locations in the case of Laasonnen et al. [9], in all cases triggering on prominent locations proved to be difficult due to monitoring imprecision and poor identification techniques. Thus, one key asset of Groupanizer is its limited set of locations particular to some situations or areas. Even though, there is no concrete limit to the number of locations, grouping them under the previously described SLM mechanism greatly reduces the number of states to be predicted (see figure 5 explanations). When a location is recorded through Groupanizer, 4 elements are simultaneously recorded, namely a name (*location*), an activity (*activity*), an SLM (*identity*) and a time (*time*). States are then represented such that $S_n \in \{L_1, L_2, ..., L_n\}$ which comprises all locations such that an ensemble of locations $L \in SLM_i$ belongs to SLM *i*.

Observations are represented by a 3-tuple *(P,A,D)*, where *P* describes the period of the day divided in 4 time spaces {*morning*, *afternoon*, *evening*, *night*}, *A* represents the activity {*dining*, *sports*, *social*, *work*, *rest*, *shop*, *commute*}, and *D* defines the current day {*Mon*, *Tue*, *Wed*, *Thu*, *Fri*, *Sat*, *Sun*}. This representation of observations creates a pool of 196 possibilities for each community, such that an observation $O_n \in \{P_i, A_j, D_z\}$. Observations describe a typical schedule like pattern information, for instance *Monday morning Working*, *Tuesday afternoon dining*, *Tuesday afternoon sports*, etc. The following figure provides a graphical overview of our model and its connections.

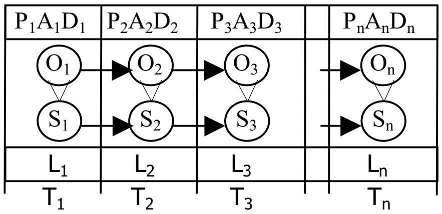

Figure 2 Groupanizer HMM model

3.3 The learning phase

All recorded data from the experimentation phase, presented in the form of table 2, was used to derive the HMM model set of parameters, namely $\lambda = (A, B, \pi)$, in accordance with the following three basic formulas $\pi(i) = P(X_n=i)$, $A(i,j) = P(X_{t+1}=j|X_t=i)$, $B(i,j) = P(Y_t=j|X_t=i)$. Hence, π (i) represents the overall probability of being at location i. Then, $A(i,j)$ represents the probability of being at destination j at time $t+1$ knowing that the user was at source i at time t. Finally, $B(i,j)$ represents the probability of observing the 3-tuple $(P,A,D) = j$ knowing that the user was at location i at time t.

3.4 The prediction phase

After computation, we want our model to identify a sequence of states that best fits a sequence of observations. Using the Viterbi algorithm, we solve for the optimal state sequence at each time t in accordance with an observation file. This being said, the Viterbi algorithm solves for the most suitable sequence at time t, and then, using this result it solves for the most suitable sequence at time $t+1$. The following 2 equations clarify the preceding statement in a mathematical sense [15].

1. $\delta_t(i) = max[\ P(S_1,S_2,\ldots,S_t=i,O_1,O_2,\ldots,O_t|\ \lambda\ )\ ]$
2. $\delta_{t+1}(j) = max[\ \delta_t(i)A(i,j)]*B(O_{t+1},S_{t+1}=j)$

In our case a sequence of initial states can be used to initialize the matrix representing parameters of equation 1 in order to take into account the history of previous displacements. The next table demonstrates the most probable sequence of locations according to a given sequence of observations.

Table 3 Location prediction

Observations			States
Period	**Activity**	**Day**	**Location**
Morning	Rest	Fri	Home
Morning	Commute	Fri	Shibakoen station
Morning	Commute	Fri	Nezu station
Morning	Work	Fri	Information center

4. Pilot Study

A pilot study was conducted for a period of two weeks -- from July 19th to August 5th 2005, overlapping with the end of classes and the first few days of summer break. This experimentation phase helped characterize the HMM models of each community for each respective user. Behavioral trends were extracted to make each model a better reflection of its community ecology.

In order to keep track of every user, personal cellular phones were used as monitoring sensors. Automatic location detection techniques could have been used, however, our methodology offered more flexibility regarding the context to be monitored, required no additional infrastructure for indoor and outdoor location sensing, and used a widely available technology in Japan. Thus, a simple email location reminder was sent to every user at an initial sampling rate of 30 minutes, which corresponds more or less to the least amount of time required to complete an activity, such as going out for lunch or coffee, buying a book, etc. This reminder linked to a server-side program querying the user for its current possible location (see figure 3). In order to do so, each of the initial 26 participants registered at http://www.groupanizer.com, a set of 5 personal prominent areas, namely the areas comprised in their PLM. For instance one could register, home, school, work, arena, and Roppongi which would represent a user's personal mesh (PLM).

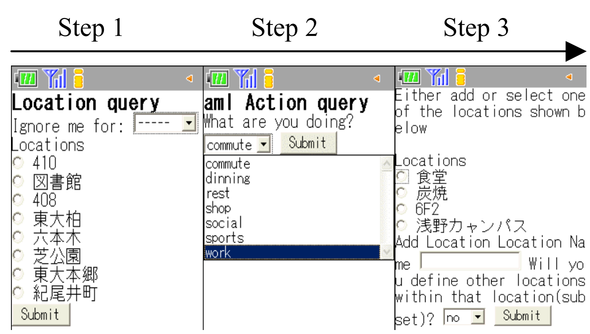

Figure 3 Location confirmation screen

5. Results and Discussion

Experimentation has shown an acceptable penetration rate taking into account that users themselves had to input their location. Even though 26 users officially registered, I would say only 13 (in orange on the graph) of them were active participants inputting a minimum of one location per day on average for a grand total of 688 hits for the 2 weeks of experimentation. The following graph shows the participation rate variation among users.

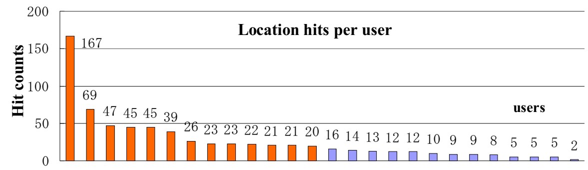

Figure 4 Location hit count per user

One interesting aspect to consider is the rate of new location input versus the actual daily location input. As suggested by the system and the following graph, it takes approximately 4 days to map the salient locations of a community. The following graph depicts the results for the "aml" SLM (AML laboratory, Tokyo University), which is where most of the locations belonged during the experiment. The average participation rate seems to be around 20 hits per day excluding the 2 overlapping weekend periods where participation was at its lowest. This is quite reflective of the activity level in the laboratory or on campus on weekends. The total new locations input for the "aml" SLM was 40 versus a total location hit for the 2 weeks experimentation of 425. Hence limiting the state number to 40 for a community of 26 individuals.

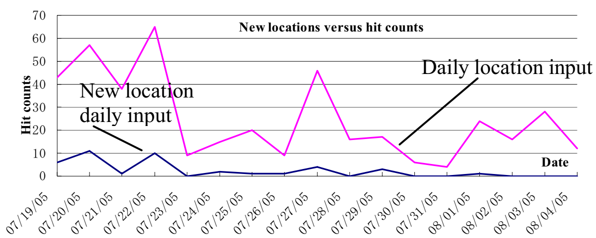

Figure 5 New locations versus hit counts

Most of the location information shared revealed that in a work environment people tend to be transparent regarding their displacements. As depicted by the following graph, despite the fact that human beings generally have three meals per day, the activity information input by users did not disclose such a common behavioral pattern, but instead locations associated to a work activity seemed to dominate the pool of input locations.

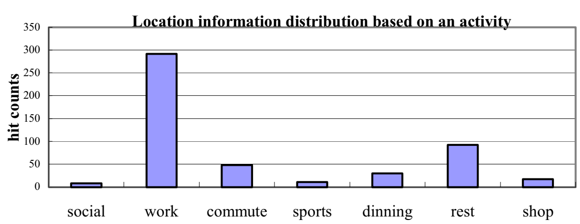

Figure 6 Location input versus activities

From the information gathered during the experimentation phase, we have noticed that the actual period of the day might have more relevance than the actual day as a location trigger. Thus our model will need to integrate a mechanism to bias probabilities. Indeed, a change in an activity was associated to a change of location in 449 cases out of 688 hits. For the remaining 239 cases where no activity change was observed, 198 hits are attributed to a work-work transition. Thus, using weighted probabilities the observation-state table (table 3) could be altered to reflect the importance of each attribute of the 3-tuple (P,A,D).

This first phase of the implementation did not include an actual prediction algorithm in the proposed system for cellular phones. The algorithm was developed using the results of the experimentation phase as shown through table 3. In order to validate the accuracy of our position prediction algorithm, a second pilot study will need to be conducted. Our current algorithm allows typical patterns to be predicted, however, when deviance exists in the sequence observed, the sequence of locations generated barely reflects the reality. This is partially due to the Viterbi algorithm maximization criteria, which does not maximize a sequence of locations but each location at time t. This being said a mechanism to compensate for inaccuracies in observation sequences such as the interpolation of transient observations, omitted in the location monitoring experimentation, could provide a way to standardize observation sequences such as the one demonstrated in table 3. Essentially, this allows the use of community's location information and recorded moments to generate a standard schedule like observation file for location prediction.

6. Related work

Location aware applications have been hailed by the telecom operators as the next killer application, however they are still facing multiple challenges. Most current cellular based applications have found a niche in areas such as people tracking and local information dispatch. [16,17,18]. In all cases, the communication channel seems to remain unidirectional, namely from an information source to a user. Moreover, initiatives like PlaceLab at Intel Research do promote location awareness application development by offering a middleware layer that uniformly binds the hardware resources available, such as GPS, GSM, Bluetooth or 802.11, to provide a current location estimate [19]. However, even though PlaceLab integrates multiple technologies to pin point locations, it relies upon a user community to map radio beacons to a specific area such as www.wiggle.net. As part of PlaceLab, Hightower et al. combine sensor data fusion and a probabilistic particle filter approach to infer the most accurate position monitoring [20]. John Krumm of Microsoft Research also compares different probabilistic methods to infer location of objects [21]. However, all these location estimation methods focus on spontaneous positioning whereas Groupanizer tries to combine multiple users location histories to extract tendencies of a community and then generate an estimation of future locations. In addition, Groupanizer does not rely on coordinates or signaling but on a generic definition of a location to predict a future contextual moment.

Reno [13] developed at Intel research, uses SMS messaging to dispatch location information. A personal location name is mapped to local GSM AP. Thus when a user needs to notify its location a list of the most probable locations are fetch in accordance with the proximity of GSM AP. Again, Reno could benefit from correlating daily moments with a GSM cell reading to provide more accurate location predictions.

7. Conclusion

This paper described Groupanizer's approach to motion behavior prediction and mapping. At the moment, our model only considers as an observation the 3-tuple (P,A,D) and does not yet comprise the collocation influence, however the prediction mechanism can already resolve simple motion behavior pattern prediction using a location's contextual information. Adding some weighted bias to the actual observation information could definitely constitute a more flexible approach to efficiently map the tendencies derived from the two weeks experiment and compensate for omitted observation sequences.

Acknowledgement

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