MobiCrowd: Simulating Crowds with Periodic and Social Mobility (Demonstration)

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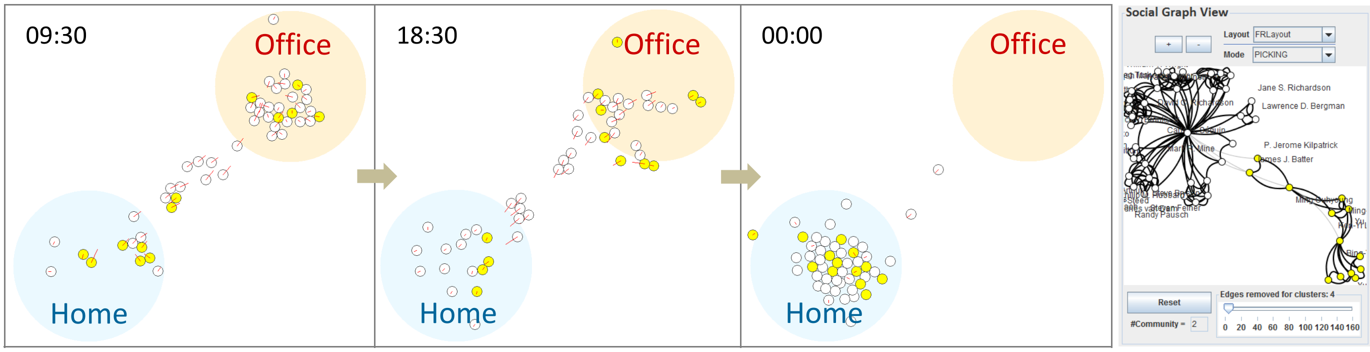


Figure 1: *MobiCrowd* simulation results. From left to right: the simulation snapshots at (a) 09:30 (b) 18:30, and (c) 00:00, in which there are two geographical areas, residential (Home) and financial (Office). Agents are colored based on (d) communities in the social network.

ABSTRACT

In this paper we develop a novel crowd simulation framework, *MobiCrowd*, which aims to generate agent-based collective flocking behaviors with periodic and social mobility. The underlying scenario is that the behaviors of people an urban area are governed by two fundamental factors: (a) spatial-temporal daily routines: stay/sleep at home, work in offices, and move between homes and offices, and (b) social interaction: those acquainted with each other might move together. *MobiCrowd* is proposed to simulate and produce the real-world phenomenon of human movements, and provide a platform to study urban dynamics and could be used in online games and animation industry.

Categories and Subject Descriptors: I.6.5 [**Simulation and Modeling**]: Model Development–*modeling methodologies*; J.4 [**Social and Behavior Sciences**]: Sociology.

Keywords: Crowd simulation, social network, social mobility, location-based social network, periodic behavior, collective intelligence

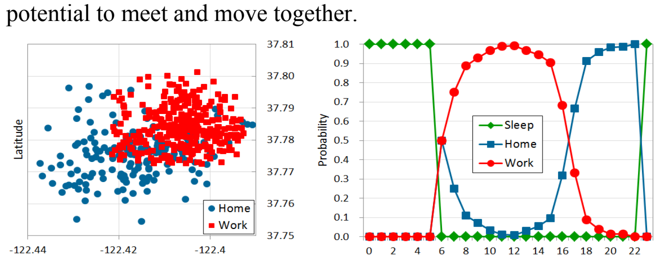
1. INTRODUCTION

Crowd simulation aims to produce collective behaviors through simulating the movement process of a number of agents. Following the Reynolds' work [6], several great models are proposed to simulate realistic crowds: Treuille et al. [7] devises *Continuum Crowds* to have smooth motions when facing moving obstacles, and Pelechano et al. [5] develop HiDAC system to deal with local motion and global wayfinding behaviors. Li et al. [3] simply simulate some collective social behaviors while human mobility is not considered. However, existing work mainly focuses on producing realistic *physical* moving behaviors of agents. The mapping to real-world *high-level* human mobility, such as periodic/daily geographical activity and social interactions, are not fully considered. In this work, by leveraging check-in data from location-based services (LBS), which provides the evidences on real-world human movement, we aim to simulate crowds with periodic and social behaviors in an *urban* environment. A novel crowd simulation framework, *MobiCrowd*, is developed. *MobiCrowd* is composed of four components: (1) *Basic Kinetics* that drives agents to move in a space, (2) *Spatial Mapping* that settles where agents locate in daily life, (3) *Temporal Journey* that controls when to alter the actions, and (4) *Social Binding* that enables those acquainted with each other to move together.

Appears in: *Alessio Lomuscio, Paul Scerri, Ana Bazzan, and Michael Huhns (eds.), Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014), May 5-9, 2014, Paris, France.*

2. MOBICROWD FRAMEWORK

Evidences from LBS. The Gowalla (http://en.wikipedia.org/wiki/Gowalla) location-based service is used to find the real-world behaviors of human mobility. For simplicity, we focus on three fundamental daily states: *work*, *home*, and *sleep*, in a certain urban area. Analyzing from the Gowalla check-in data, Figure 2 exhibits the periodic spatial-temporal evidence: users wake up at home in the morning, go to the offices to work, go home in the evening and sleep during the night. In addition, the Gowalla data is also observed to have the social mobility [2], i.e., friends have higher potential to meet and move together.



(a) (b)

Figure 2: (a) User average geographical distribution of over check-in regards in home and work states in San Francisco Bay area. (b) The temporal probability distributions for users in home, work, and sleep states.

Basic Kinetics. We extend Reynolds' model [6], consisting of separation, alignment, and cohesion forces, to be the basic kinetics of agents. Instead of treating these forces globally (i.e., all agents have the same force setting), we allow various force settings of on agents based on their current states (i.e., *work*, *home*, and *sleep*) and actions (move into/from *office*, *home*, and *sleep* states).

Spatial Mapping. Based on Figure 2(a) and other data modeling [1][2], we use two-dimensional Gaussian distribution to model the home and office coordinates of each agent into in an urban area:

$$P(l_u(t) = l_i | s_u(t)) = \begin{cases} \sim\mathcal{N}(\mu_{HS}, \Sigma_{HS}), & if\ s_u(t) = H \text{ or } S \\ \sim\mathcal{N}(\mu_W, \Sigma_W), & if\ s_u(t) = W \end{cases}$$

where $l_u(t)$ is the target location (i.e., a $\langle x, y\rangle$ pair) of agent u at time t, $s_u(t)$ is the state of agent u at time t, μ_{HS} and μ_W are the means of agents' locations in *home*/*sleep* and work states. Σ_{HS} and Σ_W are the *home*/*sleep* and *work* position covariance matrices.

Temporal Journey. Based on Figure 2(b), we consider there are three states on agents: home (H), sleep (S), and work (W). Agents could stay at home/office, sleep at home or outside, and move between home and office during the periodic simulation. We model the probability distributions $P(s_u(t) = H, S, or\ W)$ that agents change their states and actions with three truncated Gaussian distributions parameterized by the time of the day. The state transition diagram is $S \rightleftarrows H \rightleftarrows W$. Due to the page limit, we skip the mathematical details here. Integrated with Spatial Mapping, the probability of agent u's target location at time t would be:

$$P(l_u(t) = l_i) = P(l_u(t) = l_i | s_u(t) = H \text{ or } S) \cdot P(s_u(t) = H \text{ or } S) + P(l_u(t) = l_i | s_u(t) = W) \cdot P(s_u(t) = W).$$

Social Binding. A subgraph in Gowalla social network is used to construct the underlying social graph of agents. Note that one can think this is an *epitome* or a *sample* from the population of thousands/millions of people in an urban area. We design *social binding force*, $f_{sb}(u)$, to create the social mobility of agents: those acquainted with each other tend to move together:

$$\overrightarrow{f_{sb}(u)} = \sum_{v \in N_u} \left(\frac{\theta - len(u, v) + 1}{\theta} \right) \cdot \overrightarrow{d(u, v)}$$

where N_u is the set of perceived agents of u (spatially close within a threshold), $\overrightarrow{d(u, v)}$ is the direction vector from u to v, $len(u, v)$ is the shortest distance between u and v in the social graph, and θ determines the maximum hop of friends that f_{sb} takes effect (e.g. $\theta = 2$ means only friends of friends move with u).

3. SIMULATION DEMO

The simulation proceeds over daily time (i.e., hour). That says, it runs periodically from 00:00 to 23:59 and repeats day after day. Agents' moving spatial-temporal behaviors depends on the time of a day to simulate and reflect the realistic daily routine of a group of people. One can think this is an *epitome* or a *sample* from the population of thousands/millions people in an urban environment. Figure 1 shows three resulting snapshots. The generated collective behaviors consist of four parts, as described in the following.

(1) **Commuting.** First, At 09:30 and 18:30, agents leave homes and offices and move towards offices and homes respectively, in which the short red lines on agents present their current directions and speeds. We can also find that few agents wake up and go out early and few agents get up leave home late, while most of the agents do the moving action around 09:00. Similar performance from the office area to the home area appears around the evening time for off work (about 18:00). Second, during the daily movement, some agents move with higher speeds while others move slowly. We think it is realistic because people might use different means of transportation to commute between homes and offices.

(2) **In Office.** During the working hours from about 08:00 to 20:00, most agents stay closely near their offices. The result also shows that agents move slowly with limited displacements around offices. Such effect exhibits they are restricted by company regulations and can only leave the seats a while.

(3) **At Home.** Agents at homes exhibit similar behaviors as in offices. Agents walk around the neighborhood close to their homes either in the night after work or in the early morning before work. Nevertheless, there exists a difference from the working hours. According to the normal human behaviors, agents sleep at home. The result shows such sleeping action. We can observe, from about 23:00, most of the agents gradually enter into the sleeping state (i.e., the red line segments on agents disappear) and do not have any movements. They wake up at home at about from 06:00 to 08:00 regularly, with limited displacements (e.g. do exercise or eat breakfast).

(4) **Social Flocking.** During the movement between homes and offices, *sometimes* we can find agents with the same colors move together, as shown in Figure 1(d). Note that colors stand for different network communities detected by Newman's algorithm [4]. Such behavior exhibits the effect of the proposed social binding. Since agents belonging to the same communities have shorter graph distances to each other, the social blinding force will drive them to move together now and then. Note that it is not realistic if friends always walk together, and our simulation indeed reflects such behavior.

(5) **Outlier.** Three kinds of outlier agents can be identified. (a) *Temporal Outliers* stand for agents that do special actions in regular hours. For example, we can find that few agents are not on their ways to offices or homes during the commuting time, because they might go to somewhere such as watching movies or ball games for additional vacations/rests. Another scenario lies in that few agents do not sleep at night and wander outside. (b) *Spatial Outliers* refer to agents doing the regular actions in abnormal places. For instance, few agents do not work in offices but do their jobs at homes or outside regular areas. Or agents sleep outside their homes. (c) *Social Outliers* are those agents coming and going alone all the time. Even though such kind of agents has friends, they never walk together. At midnight 00:00, most of agents sleep at home (no red lines drawn on agents) while few still wander outside.

4. APPLICATIONS & ONGOING WORK

We summarize the applications of *MobiCrowd* framework in the following. (a) The spatial-temporal-social crowd dynamics provides some potential to study information diffusion for viral marketing and disease spreading for epidemics. (b) It can be used to enable more realistic robots for the industries of online games and animations. (c) We are developing a system for the geo-simulation of urban mobility during city-scale evacuation. (d) We are imposing the road networks and the transportation systems, which guides the ways of agent movements, into *MobiCrowd*.

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