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A Simulator of Human Emergency Mobility following Disasters: Knowledge Transfer from Big Disaster Data

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Abstract

The frequency and intensity of natural disasters has significantly increased over the past decades and this trend is predicted to continue. Facing these possible and unexpected disasters, understanding and simulating of human emergency mobility following disasters will become the critical issue for planning effective humanitarian relief, disaster management, and long-term societal reconstruction. However, due to the uniqueness of various disasters and the unavailability of reliable and large scale human mobility data, such kind of research is very difficult to be performed. Hence, in this paper, we collect big and heterogeneous data (e.g. 1.6 million users' GPS records in three years, 17520 times of Japan earthquake data in four years, news reporting data, transportation network data and etc.) to capture and analyze human emergency mobility following different disasters. By mining these big data, we aim to understand what basic laws govern human mobility following disasters, and develop a general model of human emergency mobility for generating and simulating large amount of human emergency movements. The experimental results and validations demonstrate the efficiency of our simulation model, and suggest that human mobility following disasters may be significantly more predictable and can be easier simulated than previously thought.

Introduction

Japan is one of the countries most affected by natural disasters. Two out of the five most expensive natural disasters in recent history have occurred in Japan, costing huge economic loss and large number of people death in the years 2011 and 1995 only. Meanwhile, according to Japan Meteorological Agency, there were over 10681 earthquakes above intensity one entire Japan in 2011 year only. These severe natural disasters usually cause large population movements and evacuations. Hence, understanding and simulating these movements following disasters are critical for planning effective humanitarian relief, disaster management, and long-term societal reconstruction. However, such kind of research is very difficult to be performed due to the fact that there is no reliable approach for accurately sensing human mobility. Recently, however, people's mobile phone data, GPS trajectories data, location-based online social networking data, and IC card data have emerged and increased explosively. The explosive increasing of these human mobile sensing data becomes the "Big Data", and offers a new way to circumvent methodological problems of earlier research for human behavior modeling because they offer high temporal and spatial resolution, are instantaneously available, have no interview bias, and provide longitudinal data for very large populations. Recenly, Song *et al.* (Song et al. 2014a; 2014b) collected data from 1.6 million GPS users in Japan

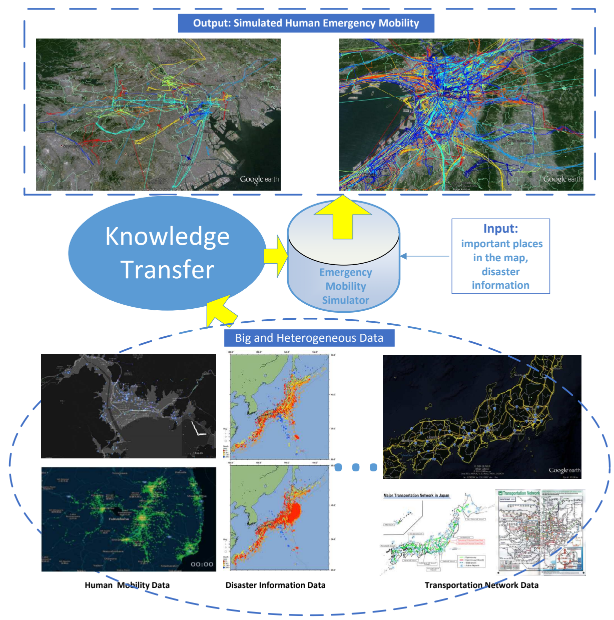


Figure 1: **Can we simulate human emergency mobility for any disaster, any place and any people?** By mining big and heterogeneous data, we aim to discover general knowledge and understand what basic laws govern human mobility following disasters. Can we develop a general model of human emergency mobility for generating or simulating large amount of human emergency movements following different disasters?

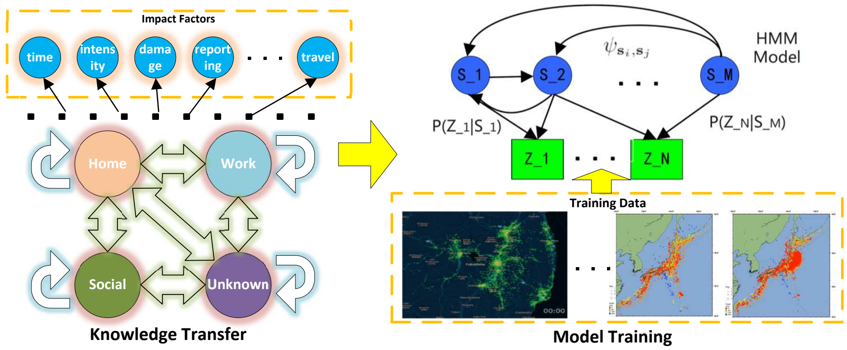


Figure 2: **Knowledge transfer and model development.** We model human activities and mobility following disasters as the random transition through its home, working location, social relationship as well as some unknown places (e.g. shelters or hotels), and the transition process will be impacted and influenced by various disaster factors. We develop a HMM based model, and utilize the big and heterogeneous data to train its parameters.

to mine and modeling human mobility during the 2011 Great East Japan Earthquake and Fukushima nuclear accident, and developed a model for predicting human behavior and mobility. However, due to the uniqueness of this disaster, their model is difficult to be applied to some different disasters (e.g. small scale one) and the places not affected by this disaster. Furthermore, their model can only be applied to the specific person that has the historical GPS records in the database. Meanwhile, due to the privacy concern, such kind of data is usually very sensitive and difficult to be published or released for further research purpose. Therefore, in this research, we aim to: *(1) discover knowledge from big disaster data and understand what basic laws govern human mobility following disasters. (2) develop a general model of human emergency mobility for generating or simulating large amount of human emergency movements following different disasters.*

In this paper, we collect big and heterogeneous data to capture and analyze human emergency mobility following different disasters in Japan (as shown in Figure 1). By mining these big data, we find that: even though human movement and mobility patterns following disasters have a high degree of freedom and variation, the majority of human mobility is based on random movement between a small set of important places. Hence, we model human activities and mobility following disasters as the random transition through its home, working location, social relationship as well as some unknown places (e.g. shelters or hotels). But the transition process will be impacted and influenced by various factors, such as intensity of earthquake, damage level, news reporting, current time, travel distance, travel time and etc. We develop a general model of human emergency behavior, and use the collected big human mobility data and disaster information data to learn how these factors will influence people's decisions. Finally, given a series of important places of people, disaster information and transportation network of the city or country, our training model can randomly simulate or generate human mobility following this disaster. Our work will have the following key characteristics that make it unique in the world:

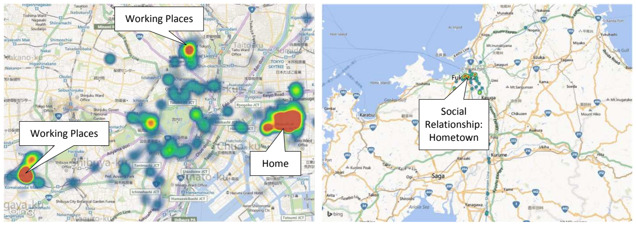
- **Big and heterogeneous data:** 1.6 million users' GPS records in three years, 17520 times of Japan earthquake data in four years, news reporting data, transportation network data and etc.
- **A general model of human emergency mobility:** our model can randomly simulate or generate human mobility following disasters, it can be applied to any people, any place and any disaster.

The remainder of this paper is structured as follows: Section 2 introduces our big and heterogeneous data source. Section 3 describes the knowledge transfer from data and model development. Section 4 provides the details on human emergency mobility simulation and generation. Experimental results are presented in Section 5. Related work is briefly reviewed in Section 6, and the paper is finally summarized in Section 7.

Heterogeneous Data Source

In this research, we utilize big and heterogeneous data source to understand human mobility following disasters, and they can be summarized as follows:

- Human mobility data: we collected GPS records of approximately 1.6 million anonymized users throughout Japan from 1 August 2010 to 31 July 2013. To manage these data, we utilized five computer to build up a Hadoop cluster, which contained 32 cores, 32GB memory, 16TB storages, and was able to run 28 tasks at the same time. It can provide indexing, retrieval, editing and visualization services.
- Disaster information data (earthquake and tsunami): we collected 17520 times of earthquake data throughout Japan from 1 January 2010 to 31 December 2013. These data contains occurrence time, earthquake hypocentral location, earthquake magnitude, earthquake intensity for impacted places, damage level (1-7) (e.g. destroyed buildings and people death by the earthquake or tsunami) and etc.



(a) Distribution of geographic location on woking days

(b) Distribution of geographic location on important holidays

Figure 3: **Distribution of geographic location for one of the authors.** This figure shows the distribution of geographic location for specific person (one of the authors of this paper) during normal times. The color denotes the probability of staying location of this person at a specific time period; warmer ones indicate higher probability. Figure (a) shows this distribution on working days, and Figure (b) shows the cases on some important holidays (e.g. national holiday, New Year Festival, Christmas day).

- Disaster reporting data: we collected government declarations as well as news reports from mainstream medias in Japan and all over the world for large-scale disasters (e.g 2011 Great East Japan Earthquake). Based on these information, we empirically divided these reporting and declarations into four levels to measure the disasters, e.g. one level means not serious from the reporting, and four level means extremely serious.
- Transportation network data: we collected the road network data and metro network data of main cities in Japan. These data contains road structure and POI information.

Knowledge Transfer and Model Development

By performing some empirical analysis on human mobility data following disasters, we find that: even though human movement and mobility patterns following disasters have a high degree of freedom and variation, the majority of human mobility is based on random movement between a small set of important places, such as home location, working location, social relationship (friends' house, hometown and etc.) and some unknown places (e.g. shelters, hotels and etc.). Meanwhile, these mobility patterns will also be impacted and influenced by various kinds of factors (as shown in Figure 2). For instance, if a small earthquake with low intensity occur at midnight, people may stay at home and go back to sleep. In contrast, if a big earthquake occur at midnight and cause some building destructions, people may screw out of the house and find some safe places to stay, but they need to consider the travel distance or travel time. But if a very huge earthquake (such as 2011 Great East Japan Earthquake) occur and become the composite disaster accompanied with many negative news reporting, people may leave their living city and find a safe place (e.g. hometown) far from the disaster. Hence, in this section, we aim to understand how these factors will influence and govern human mobility following disaster, and extract general knowledge of human disaster behaviors by mining big and heterogeneous data.

Important Places Discovery

To model and understand human behavior and mobility following disaster, we need to discover and recognize important places in peoples daily life, e.g. home, working places, and places of important social relationships (e.g. hometown, parents, relatives and good friends). In this research, we utilized the mobility data to compute distribution of geographic location (X. Song and Shibasaki 2013b) for individual people (as shown in Figure 3). Based on the analysis of this distribution with time, it is easy for us to find and recognize some important places of individual people. For example, the highest frequency staying place by daylight on working day is usually peoples working place, and the one in night is usually peoples home (as shown in Figure 3-a). Meanwhile, some high frequency visited places on the weekend and some important holiday (e.g. national holiday, New Year Festival, Christmas day) are recognized as the peoples important social relationships (as shown in Figure 3-b).

Model Development and Learning

Preliminaries: Consider a set of individual people's activities $Activity = \{act_1, act_2, ..., act_n\}$ after the disasters, and each activity $act_i = \mathbf{l}_1 \rightarrow \mathbf{l}_2 \rightarrow ... \rightarrow \mathbf{l}_m$ denotes a series of m location transfer with the disaster information. Each location $\mathbf{l}$ is a tuple in the form of $\mathbf{l} =< uid, time, label, latitude, longtitude, distance, intensity, damage, reporting >$, where uid is the id of people, $time$ is the current time, $label$ specify the people's important places, such as home location, working location, places of important social relationships and unknown places. Here, $latitude$ and $longtitude$ specify the geographic position of this location, $distance$ is the distance from the earthquakes, $intensity$ is the seismic or intensity scale of the earthquake at this location, $damage$ is the damage level of this location, and $reporting$ is the government declarations and news reporting level. Therefore, our goal is to learn a general model from $Activity$. Given a series of people's important places and disaster information, we want to randomly simulate or generate people's location transition sequences with the probability.

HMM based Model: In this study, given a set of disaster information $\mathbf{Z} = \{\mathbf{z}_1, \mathbf{z}_2, ...\mathbf{z}_N\}$, such as intensity of earthquake, damage level, news reporting, current time, travel distance, travel time, we model human activities and mobility following disasters as the random transition through a series of state $\mathbf{S} = \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_M\}$, such as home location, working location, social relationship, some unknown places. In this study, we use hidden Markov model (HMM) (J. Ye and Cheng 2013; Zucchini and MacDonald 2009) to model dependency between these states, and the overall behavior model with its graphical representation is shown in Figure 2.

In our study, the following three key parameter components of HMM model need to be learned: (1) initial state probability $\phi_{\mathbf{s}_i}$ for each hidden states $\mathbf{s}_i \in \mathbf{S}$; (2) state transition probability $\psi_{\mathbf{s}_i,\mathbf{s}_j}$ from the hidden states $\mathbf{s}_i$ to $\mathbf{s}_j$; and (3) state-dependent output probability $P(\mathbf{z}_j|\mathbf{s_i})$, which determines the probability of the people's mobility $\mathbf{z}_j \in \mathbf{Z}$ given the hidden behavior state $\mathbf{s}_i \in \mathbf{S}$.

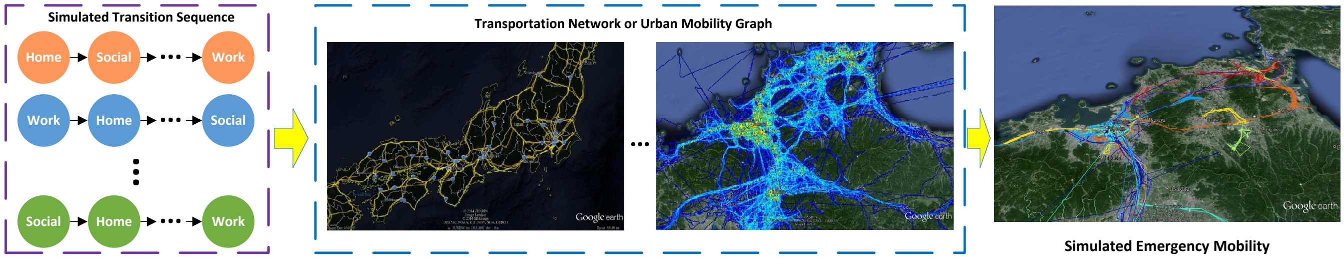


Figure 4: **Emergency mobility simulation.** Based on our training HMM model, we randomly simulate the location transition sequences. Then we utilize the transportation network or pre-trained urban mobility model to plan the traveling routes, and finally generate the human emergency movements following disasters.

Model Learning: To learn the overall behavior model, we need to estimate the key parameters of HMM as the discussion above, and a suitable solution is to use EM approach which aims at maximizing the likelihood of the location transfer sequences. In our study, the overall likelihood should be summed over all possible location transfer through the underlying hidden states, and is able to be computed by:

$$P(\mathbf{Z}_{1:T}) = \sum_{\mathbf{S}_1=\mathbf{s}_1}^{\mathbf{S}_M} \dots \sum_{\mathbf{S}_T=\mathbf{s}_1}^{\mathbf{S}_M} \phi_{\mathbf{S}_1} \prod_{t=2}^{T} \psi_{\mathbf{S}_{t-1},\mathbf{S}_t} \prod_{t=1}^{T} P(\mathbf{Z}_t|\mathbf{S}_t). \tag{1}$$

Here, we assume the HMM is time-homogeneous, and state transition probabilities and state-dependent output probabilities do not change with time t.

According to (Zucchini and MacDonald 2009), we reformulate Equation (1) as:

$$P(\mathbf{Z}_{1:T}) = \Phi \mathcal{P}_{\mathbf{Z}_1} \Psi \mathcal{P}_{\mathbf{Z}_2} \dots \Psi \mathcal{P}_{\mathbf{Z}_T} \mathbf{1}^{\top}, \tag{2}$$

which is expressed by matrix multiplications to reduce the computational cost. Here, Φ is a $1 \times M$ initial state distribution vector, Ψ is a $M \times M$ hidden state transition matrix where $\Psi_{ij} = \psi_{\mathbf{s}_i,\mathbf{s}_j}$, and $\mathcal{P}_{\mathbf{Z}_T}$ is a $M \times M$ diagonal matrix with $P(\mathbf{Z}_t|\mathbf{s}_i)$ on the diagonal and other entries as 0. Then we can use Baum-Welch algorithm (Baum et al. 1970) to estimate the hidden state transition probabilities and the state-dependent output probabilities.

To decide the right number of hidden states M in learning the HMM, we use *Bayesian Information Criterion* (BIC) (Schwarz and others 1978) to evaluate the HMM with different state numbers, and a smaller BIC value always leads to better model fitness.

Emergency Mobility Simulation

Given a series of important places of people and the disaster information, we aim to randomly simulate and generate its emergency mobility following this disaster (as shown in Figure 4). There are mainly two stages for the simulation process: (1) based on the training HMM behavior model, we randomly generate location transition through its important places; (2) given the location transition sequences, we use the transportation network or pre-trained urban mobility graph (Song et al. 2014a) to plan the traveling routes. Hence, in this section, we will present details on how to simulate human emergency mobility following different disasters.

Location Transition Simulation

To randomly generate person's location transition sequence following disasters, we utilize particle filter (Doucet, Godsill, and Andrieu 2000) approach to simulate this process. The basic idea behind a particle filter is very simple. Starting with a weighted set of samples $\{w_t^{(k)}, \mathbf{s}_t^{(k)}\}_{k=1}^{K}$ approximately distributed according to $p(\mathbf{s}_{t-1}|\mathbf{z}_{t-1})$, new samples are generated from a suitably designed proposal distribution $q(\mathbf{s}_t|\mathbf{s}_{t-1}, \mathbf{z}_t)$. To maintain a consistent sample, the new importance weights are set to

$$w_t^{(k)} \propto w_{t-1}^{(k)} \frac{p(\mathbf{z}_t|\mathbf{s}_t^{(k)})\psi_{\mathbf{s}_t^{(k)},\mathbf{s}_{t-1}^{(k)}}}{q(\mathbf{s}_t^{(k)}|\mathbf{s}_{t-1}^{(k)}, \mathbf{z}_t)}, \sum_{k=1}^{K} w_t^{(k)} = 1. \tag{3}$$

Hence, the overall simulation process is present as follows:

1. Initialization:
Generate K weighted set of samples $\{w_t^{(k)}, \mathbf{s}_t^{(k)}\}_{k=1}^{K}$ from the learnt initial state probability $\phi_{\mathbf{s}_i}$ of our trained HMM.

2. Resampling:
Resample K particles from the particle set $\mathbf{S}_t$ using weights of respective particles.

3. Location Transition Simulation:
Simulate the state transition of the particle set $\mathbf{S}_t$ with the learnt transition probability $\psi_{\mathbf{s}_i,\mathbf{s}_j}$ of our trained HMM.

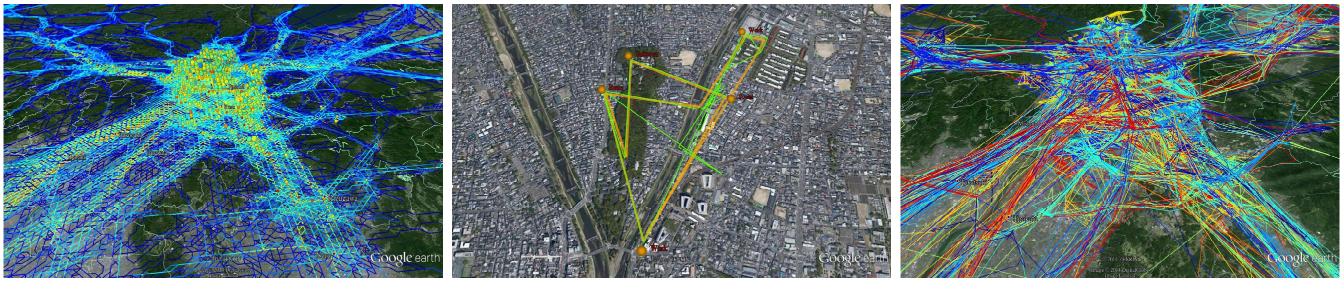
4. Weighting:
Recalculate the weight of $\mathbf{S}_t$ by using Equation (3). Here, we utilize the learnt observation model $P(\mathbf{Z}_{1:t}|\mathbf{S}_t)$ of our trained HMM as the proposal distribution in Equation (3).

5. Behavior Selection :
Select person's transition behavior by finding the highest weight one in the particle set $\mathbf{S}_t$.

6. Iteration:
Iterate Steps 2, 3, 4, and 5 until convergence.

Mobility Simulation

Given the location transition sequences of people following disasters, there are two ways to simulate its traveling routes. For the small earthquakes, we can directly use the transportation network (e.g. road network data and metro network) of cities to plan people's traveling routes. But for the large-scale earthquakes, the public transportation systems are usually unavailable. Hence, we use the pre-trained urban mobility graph (Song et al. 2014a) to plan the traveling routes (as shown in Figure 4).



(a) Urban mobility graph for Kyoto (b) Simulation results of single person (c) Simulation results of large number of persons

Figure 5: **Visualization of simulation results.** This figure shows the example of our simulation results for Kyoto. Here, we use the pre-trained urban mobility model to plan the routes. Fig.a shows the urban mobility graph of Kyoto. Fig.b shows the example of simulation results for the single person. Fig.c shows the example of simulation results for large number of persons in Kyoto.

To effectively plan people's traveling routes by considering various disaster factors, we train a decision model by using Markov Decision Process (MDPs) (Puterman 1994). In our problem, the transportation network or urban mobility graph provide us a deterministic MDP, the nodes are able to be seem as *state*, the edge is the *action*, and the *path* is the people's movements following the earthquake. These movements are parameterized by their path feature $\mathbf{f}_\zeta$. For instance, a person's movements can be described by: travel through node A ($dens = 0.37$, $type = residential$) to node B ($dens = 0.58$, $type = commercial$), and finally stayed in node C ($dens = 0.75$, $type = administrative$) with route 1 ($frq = 0.37$, $time = 0.58$) ($A \rightarrow B$) and route 2 ($frq = 0.29$, $time = 0.62$)($B \rightarrow C$), where $dens$ is the region population density, $type$ the region types (e.g. residential, commercial and etc.), frq the travel frequency of the route, $time$ is the travel time of the route. Hence, we need to utilize all the population trajectories to train a MDPs model that is able to optimally demonstrate these people's movements after the earthquake. Obviously, this is an *Inverse Reinforcement Learning* problem. In this study, we utilize the *Maximum Entropy Inverse Reinforcement Learning* algorithm (B. D. Ziebart and Dey 2008b; 2008a) to train the overall decision model.

Finally, given person's location transition sequence, its mobility can be easily simulated by performing the Markov model route planning. In our study, we assume that people usually will find a safe and fast route (e.g. high frequency visited route and low travel time) for evacuation following the disasters. Hence, we employ the route planning using the destination-conditioned Markov Model (Simmons et al. 2006). This model recommends the most probable route satisfying origin and destination constraints.

Experimental Results

Based on the disaster information data (space and time), we selected human movements (GPS trajectory) in 24 hours following each earthquake from our human mobility database, and the selected geotropical regions were the places where the earthquake intensity was above one. These GPS trajectories, the related disaster information and the disaster reporting information formed the training and testing dataset. We randomly selected 80% of the data for the model training, and used the remaining 20% data for testing and evaluation. We then converted the GPS trajectories in the training set to the sequence of important places transition as the discussion in Section 3 to prepare the training samples. In the training process, we found that the majority of training data were from some very small-scale earthquake (e.g. earthquake intensity is below 3). To balance the training samples of large and small scale disasters, we randomly selected 20% data from small-scale disasters set, and use them with large-scale disaster data to form the new training sample dataset. In this section, we present experimental results and evaluation of model for human emergency mobility simulation.

Simulation Results

To simulate human emergency mobility following disasters, users need firstly to select the important places in the map, and then input the disaster information (e.g. occurrence time, earthquake hypocentral location, earthquake intensity at this region, damage level and etc.), and our simulator can automatically simulate possible movements of this person. To show the performance, here we used the real information in the testing dataset as the input. Figure 5 shows the sample results of our simulator. From Fig.5-b, we can see that our simulation results are very similar the real movements of this person following a specific disaster.

Performance Evaluation

Evaluation metrics: To evaluate the accuracy of the simulated mobility of people, we used three different metrics discussed in (B. D. Ziebart and Dey 2008a). The first compared the model's most likely simulated trajectory (trajectory with the highest probability) with the actual demonstrated trajectory in the testing set and evaluated the amount of route distance shared. The second shows what percentage of the testing trajectories match at least 90% (distance) with the model's simulated one. The final metric measures the average log probability of mobility in the training set under the given model.

Table 1: Performance Evaluation

Algorithm	Matching	90% Matching	Log-Prob
Our Model	65.26%	45.33%	-7.13
MF	58.23%	39.62%	-7.97
GM	51.22%	33.16%	-8.21
PMM	63.18%	42.69%	-7.33

Baseline models: We considered three non-trivial baseline models for comparison. (1) *Most Frequented Location Model (MF)*: For every hour of the day, this model simulates the most likely (most frequent visited) place of a particular people. Despite its simplicity, this model is very strong baseline. Lu *et al.* (X. Lu and Holme 2012) also used this model to predict population mobility after the 2010 Haitian earthquake. (2) *Gaussian Model (GM):* This model has been proposed by Gonzales *et al.* (MC. Gonzalez and Barabasi 2008), and it models human movements as a stochastic process centered around a single point. This model is static in time and captures the scale of a person's movements more than anything else. (3) *Periodic Mobility Model (PMM):* This model is built on the intuition that the majority of human movement is based on periodic movement between a small set of locations. As the state-of-the-art methods, it has been proposed by Cho *et al.* (E. Cho and Leskovec 2011), which is able to predict the locations and dynamics of future human movements. For training these baseline models, we retrieved the GPS data in three months from our mobility database by using person ID in the testing set, and use them to train the final model. Then, we used these baseline models to predict human next visited places following the disasters, and then used the transportation network to plan the final traveling routes of people.

Performance evaluation: We compared the performance of our model with the performance of the baselines, and table 1 shows their performance. The baseline models are trained by particular people's historical movements, and can only be applied to specific person. In contrast, our model is a general mobility model, and can be applied to any person. From this table, we can see that the performance of our model is very similar to PMM model, and has a much better performance than the other two models. Obviously, our simulator is more powerful for simulating human emergency mobility than these competing methods that are used for predicting or simulating human mobility during normal times.

Related Work

Recently, a number of studies on human mobility patterns during disasters have been proposed (M. Moussaid and Helbing 2009; Hahm and Lee 2009), mainly focusing on small-scale and short-term emergencies (e.g. crowd panics and fires). However, research on the dynamics of population movements on a national scale during large-scale disasters (e.g. earthquakes, tsunamis, and hurricanes) is very limited (X. Lu and Holme 2012), likely the result of difficulties in collecting representative longitudinal data in places where infrastructure and social order have collapsed (JP. Bagrow and Barabasi 2011; L. Bengtsson 2011) and where study populations are moving across vast geographical areas (X. Lu and Holme 2012). Recently, the big auto-mobile sensor data (e.g. mobile phone data, GPS data, location-based social network data and etc.) offer a new way to analyze and model population movements for very large populations (CM. Song and Barabasi 2010; MC. Gonzalez and Barabasi 2008; X. Lu and Holme 2012; JP. Bagrow and Barabasi 2011; C. Song and Barabasi 2010; N. Eagle and Lazer 2009). Meanwhile, human mobility or trajectory data mining (Backstrom, Sun, and Marlow 2010; Giannotti et al. 2007; E. Cho and Leskovec 2011; J. Ye and Cheng 2013; Z. Li and Nye 2010; Scellato, Noulas, and Mascolo 2011; X. Song and Shibasaki 2013a; 2013b; Yuan et al. 2013) have become a very hot topic in various research fields.

More Recently, Song *et al.* (Song et al. 2014a; 2014b) collected the data from 1.6 million GPS users in Japan to mine and model population evacuations or mobility during the 2011 Great East Japan Earthquake and Fukushima nuclear accident, and demonstrated that the prediction of large population movements or individual person after large-scale disaster was possible. However, due to the uniqueness of this disaster, their model is difficult to be applied to the places outside of Japan or places not affected by this disaster. Furthermore, their model can only be applied to the specific person that has the historical GPS records in the database. Thus, in this research, we firstly propose a general model of human emergency mobility that can be applied to any people, any place and any disaster.

Conclusion

In this paper, we collect big and heterogeneous data to capture and analyze human emergency mobility following different disasters in Japan, and develop a general model of human emergency mobility for generating or simulating large amount of human emergency movements following disasters. The experimental results and validations demonstrate the efficiency of our simulation model, and suggest that human mobility following disasters may be easier simulated than previously thought.

We note the limitations within our study. Because our training data was very huge, we found that with the increasing amount of training data, the performance of our model will face some bottlenecks. In the future, we will try to build up Deep Belief Net and utilize the deep learning technology to model large amount of human emergency movements.

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