Prediction and Simulation of Human Mobility Following Natural Disasters

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In recent decades, the frequency and intensity of natural disasters has increased significantly, and this trend is expected to continue. Therefore, understanding and predicting human behavior and mobility during a disaster will play a vital role in planning effective humanitarian relief, disaster management, and long-term societal reconstruction. However, such research is very difficult to perform owing to the uniqueness of various disasters and the unavailability of reliable and large-scale human mobility data. In this study, we collect big and heterogeneous data (e.g., GPS records of 1.6 million users[1] over 3 years, data on earthquakes that have occurred in Japan over 4 years, news report data, and transportation network data) to study human mobility following natural disasters. An empirical analysis is conducted to explore the basic laws governing human mobility following disasters, and an effective human mobility model is developed to predict and simulate population movements. The experimental results demonstrate the efficiency of our model, and they suggest that human mobility following disasters can be significantly more predictable and be more easily simulated than previously thought.

29

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1. INTRODUCTION

Japan is one of the countries most severely affected by natural disasters. Two of the five most devastating natural disasters in recent history (1995 and 2011) have

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occurred in Japan, and these have resulted in heavy economic losses and numerous deaths. According to the Japan Meteorological Agency (JMA), over 10,681 earthquakes having an intensity of more than one occurred throughout Japan in 2011 alone. These severe natural disasters usually cause large population movements and evacuations. Therefore, understanding these movements is critical for planning effective humanitarian relief, disaster management, and long-term societal reconstruction for the governments all over the world. "Even though human movement and behavior patterns have a high degree of freedom and variation, they also exhibit structural patterns due to geographic and social constraints" [Cho et al. 2011]. In particular, after large-scale disasters, the population mobility pattern seems to be highly influenced by several disaster states and various factors such as the disaster intensity, damage level, government declarations, and news reports [Song et al. 2013b]. Lu et al. [2012] found that "population mobility patterns following the 2010 Haitian earthquake disaster were highly correlated with their daily movements prior to the event," and they concluded that population movements after large-scale disasters may be significantly more predictable than previously thought. Song et al. [2013b] found that after the Great East Japan Earthquake and Fukushima nuclear accident, in regions that were instantaneously impacted by the earthquake and tsunami, large numbers of people sought immediate refuge in nearby cities or government shelters. However, in regions that were more impacted by the release of nuclear materials, the evacuation patterns were highly influenced by government declarations and news reports.

Even though the aforementioned are some of the fundamental questions or hypotheses on human behavior and mobility after natural disasters, answers to these questions largely remain unknown mostly because there is no reliable approach for accurately sensing human mobility. Recently, however, mobile phone data, GPS trajectory data, location-based online social networking data, and IC card data have emerged and increased explosively. These data offer high temporal and spatial resolution to circumvent the methodological problems faced in earlier research on human behavior modeling, and they provide longitudinal and latitudinal data for very large populations. Therefore, in this research, we aim to study human mobility following natural disasters from two aspects: *(1) uncover the basic laws governing human mobility by mining big data and (2) build an effective model to predict and simulate human mobility*.

In this study, we collected big and heterogeneous data to capture and analyze human mobility following natural disasters in Japan. By mining these big data, we found that the population behavior and mobility after large-scale disasters (e.g., the Great East Japan Earthquake and Fukushima nuclear accident) correlated with their mobility patterns during normal times, and they were also highly impacted by their social relationship, disaster intensity, damage levels, government-appointed shelters, government declarations, and movements of large population flows (as shown in Figure 1). Based on these findings, we tried to model the relationship between human behavior and these influencing factors during disasters and developed a human mobility model for predicting population movements following natural disasters. In our work, we decomposed the prediction problem into two subproblems (as shown in Figure 2): (1) given the current disaster state, influencing factors, and observed human movements, predict the possible behavior in the next step, and then (2) predict the possible movements and transportation mode given the estimated behavior distribution. Furthermore, we extracted general knowledge of human disaster behaviors based on these data and developed a knowledge transfer model to simulate human mobility during disasters for any people, any place, and any disaster. Our work will have the following key characteristics that make it unique in the community:

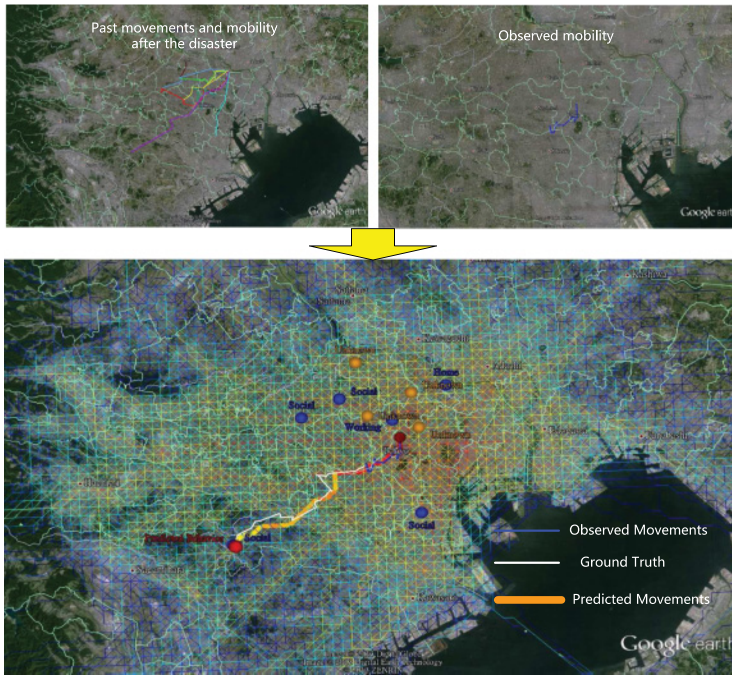


Fig. 1. **Prediction of human behavior and mobility following large-scale disasters.**[1] Can we predict human behavior and movements during disasters by modeling their past movements? If some disaster occurs in the future, given a person's currently observed movements, where will this person go in the next time period? What will this person's traveling route be?

—**Big and heterogeneous data:** GPS records from 1.6 million users over 3 years,[1] Japan earthquake data over 4 years, news reporting data, transportation network data, and so forth.

—**An effective model of human mobility during disasters:** Our model can predict and simulate human emergency mobility following natural disasters. To the best of our knowledge, this work is the first to model human behavior during various disaster states, and it can accurately predict and simulate population movements following different disasters.

The remainder of this article is structured as follows. Section 2 briefly reviews related works. Section 3 introduces heterogeneous data and the empirical analysis of population mobility patterns following the Great East Japan Earthquake and Fukushima nuclear accident. Section 4 describes the human behavior model based on our empirical analysis and the prediction of human behavior after disasters. Section 5 provides details about urban mobility model learning and the prediction of human mobility. Section 6 introduces knowledge transfer from the big disaster data and our simulation

[1]We used "Konzatsu-Tokei (R)" from ZENRIN DataCom. "Konzatsu-Tokei (R)" data refers to people flows and it is collected from mobile phones with the enabled AUTO-GPS function under users' consent and agreement, through the "docomo map navi" service provided by NTT Docomo. The statistics data is anonymized and aggregated so that individual information can never be retrieved. The anonymization and aggregation were made by NTT Docomo based on the request of Zenrin DataCom Co. Original location data is GPS data (latitude, longitude) sent in about every a minimum period of 5 minutes and does not include any personal information, such as gender or age. The processing of raw GPS data for this study was conducted by NTT Docomo.

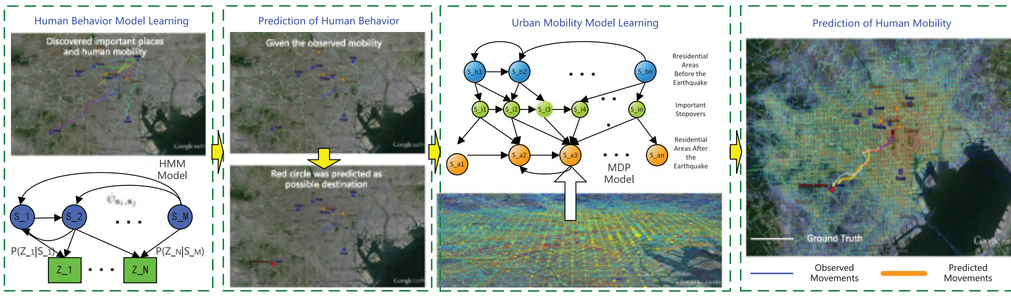


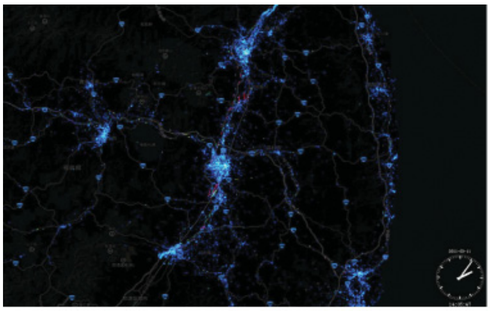
Fig. 2. **Overview of the approach.**[1] Our approach decomposes the prediction problem into two subproblems: (1) First, we use people's past movements during disasters and places important to them to train a hidden Markov model (HMM)-based human behavior model. Then, given a person's current observed movements and disaster states, our model predicts their possible behavior in the next time period. (2) Second, we use the entire collected population movements of a specific urban area and their transportation mode label to train the urban mobility model. Then, our model predicts a person's possible movements and transportation mode given the predicted behavior in the next time period.

model. Section 7 presents the experimental results. Finally, Section 8 summarizes this article.

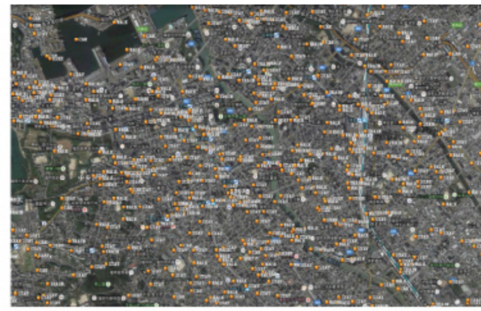
2. RELATED WORKS

Recently, many studies have investigated human mobility patterns following disasters [Moussaid and Helbing 2009; Hahm and Lee 2009], with a focus on small-scale or short-term emergencies (e.g., crowd panics, fires, etc.). However, research on the dynamics of population movements on a national scale following large-scale disasters (e.g., earthquakes, tsunamis, and hurricanes) is very limited [Lu et al. 2012]. In this regard, automobile sensor data [Song et al. 2010; Gonzalez et al. 2008; Lu et al. 2012; Bagrow et al. 2011; Song et al. 2010; Eagle et al. 2009] and social network data [Wang et al. 2014] offer a new way to circumvent the methodological problems faced in earlier research. Furthermore, human mobility or trajectory data mining [Chen et al. 2010, 2011; Giannotti et al. 2011; Li et al. 2010; Yuan et al. 2012; Backstrom et al. 2010; Giannotti et al. 2007; Li et al. 2010; Scellato et al. 2011; Zheng et al. 2009; Li et al. 2010; Xue et al. 2013; Su et al. 2013; Yuan et al. 2013; Ge et al. 2014; Zhu et al. 2014; Ying et al. 2013; Zheng et al. 2014] has gained much interest in various research fields. Zheng et al. [2009] aimed to mine interesting locations and travel sequences from GPS trajectories. Cho et al. [2011] proposed a periodic mobility model (PMM) for predicting the dynamics of future human movements by using check-in data. Ye et al. [2013] proposed an HMM-based human behavior model to predict human activity from check-in data. Yuan et al. [2013] proposed a graph-based model for summarizing population mobility.

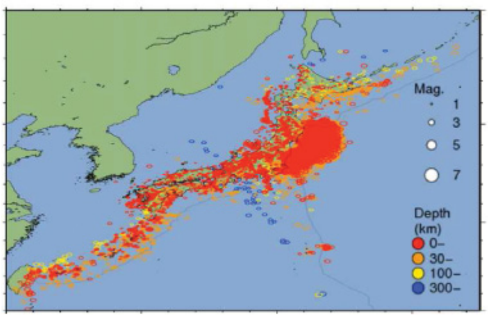
More recently, Lu et al. [2012] collected data from 1.9 million mobile users in Haiti to analyze population displacement after the 2010 Haitian earthquake and concluded that population movements during disasters may be significantly more predictable than previously thought. Gao et al. [2014] collected cell phone data to study people's communication patterns during anomalous events. Song et al. [2013b, 2014a] collected data from 1.6 million GPS users in Japan to mine and model population evacuations during the 2011 Great East Japan Earthquake and Fukushima nuclear accident and demonstrated that the prediction of large population movements after a large-scale disaster was very possible. However, owing to the lack of a powerful human behavior model that can fully depict how different disaster factors will influence population mobility patterns, they cannot accurately predict behavior or mobility for an individual



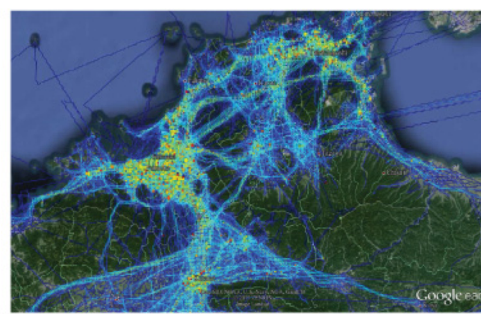
(a) GPS Data: human mobility in Fukushima



(b) Mobility data with transportation mode label



(c) Disaster Data: earthquakes in Mar. 2011



(d) Transportation Data: Fukuoka mobility graph

Fig. 3. **Big and heterogeneous data source.**[1] This figure shows the heterogeneous data source of our system. (a) Human mobility in Fukushima during the Great East Japan Earthquake and (b) human mobility in Osaka with the transportation mode label. (c) Information on earthquakes throughout Japan in March 2011. (d) Urban mobility graph of Fukuoka. The edge color indicates the edge parameters. Here, it shows the travel frequency after the disasters; warmer colors indicate higher travel frequency, and these values are normalized from 0 to 1.

person. Thus, in this study, we first try to develop a concise human behavior model for accurately predicting and simulating human mobility after natural disasters.

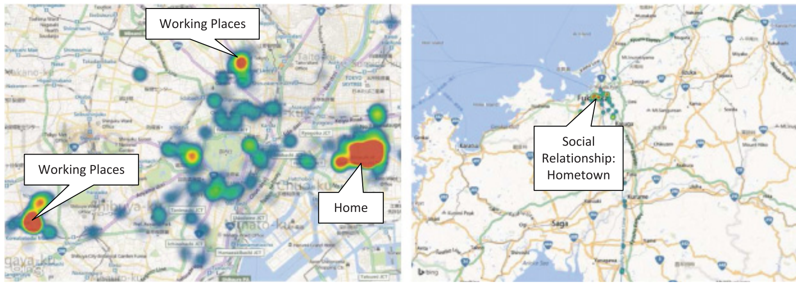
This article is an extended version of Song et al. [2014b, 2015]. Compared to the previous version, we have updated the human mobility data source by adding transportation mode labels (e.g., stay, walk, bicycle, car, train) and considered people's transportation patterns to predict their mobility following disasters. In addition, we propose to use a multimodal route planning approach [Delling et al. 2013; Bast et al. 2013] to simulate human mobility in transportation networks during small-scale disasters.

3. HETEROGENEOUS DATA AND EMPIRICAL ANALYSIS

3.1. Heterogeneous Data Source

In this study, we utilized big and heterogeneous data sources to understand human behavior and mobility following natural disasters; these were summarized as follows:

Human mobility data: We collected GPS records of approximately 1.6 million anonymized users[1] throughout Japan from August 1, 2010, to July 31, 2013 (as shown in Figure 3(a)). To manage these data, we utilized five computers to build up a Hadoop cluster that contained 32 cores, 32GB memory, and 16TB storage and that could run 28 tasks simultaneously. It can provide indexing, retrieval, editing, and visualization services. Compared to our previous research [Song et al. 2014b, 2015], the transportation mode labels (e.g., stay, walk, bicycle, car, train) of people were added to the data source (as shown in Figure 3(b)).



(a) Distribution of geographic location on woking days

(b) Distribution of geographic location on important holidays

Fig. 4. **Distribution of geographic location for one of the authors.**[1] This figure shows the distribution of geographic locations for a specific person (one of the authors of this article) during normal times. The color denotes the probability of this person staying at a location during a specific time period; warmer colors indicate higher probability. Figure (a) shows this distribution on working days, and Figure (b) shows the same on important holidays (e.g., national holiday, New Year Festival, Christmas day).

Disaster information data: We collected earthquake data throughout Japan from January 1, 2010, to December 31, 2013 (as shown in Figure 3(c)). These data contain the occurrence time, earthquake hypocentral location, earthquake magnitude, earthquake intensity for impacted places, damage level (1–7) (e.g., destroyed buildings and deaths caused by the earthquake or tsunami), and so forth.

Disaster reporting data: We collected government declarations as well as news reports from mainstream media in Japan and all over the world for large-scale disasters (the Great East Japan Earthquake was the only large-scale one we considered in this study). Based on this information, we invited three persons (two with an academic background and one without any academic background) to empirically divide these declarations and reports into four levels to measure the disasters. Here, level one means that the government declarations and reports were not serious, whereas level four means that they were extremely serious. For instance, if the government requires the victims to leave their hometowns, the level should be four. In contrast, if the government does not issue any administrative orders, the level should be one.

Transportation network data: We collected the road network data and metro network data for the main cities in Japan. These data contain road structure and POI information.

3.2. Empirical Analysis of Human Disaster Behavior

Discovery of important places: Although people are now traveling farther and faster than before, they still spend much of their time at a few important places. To analyze people's behavior during a disaster, we need to discover and recognize important places in people's lives, for example, home, working places, and places of important social relationships (e.g., hometown, parents, relatives, and good friends). In this study, we utilized GPS data for several months (August 1, 2010, to March 11, 2011) before the Great East Japan Earthquake to compute the distribution of geographic locations [Song et al. 2013b; Tan and Kumar 2005] for individual people (as shown in Figure 4). Based on the analysis of this distribution with time, it is easy for us to find and recognize some important places for individual people. For example, during the daytime on a working day, people are usually at their workplace with the highest frequency, and during the night, they are usually at home (as shown in Figure 4(a)). Meanwhile, some high-frequency visited places on weekends and some important holidays (e.g., national holiday, New Year, Christmas) are recognized as people's important social relationships (as shown in Figure 4(b)). Furthermore, we also computed people's geographic location

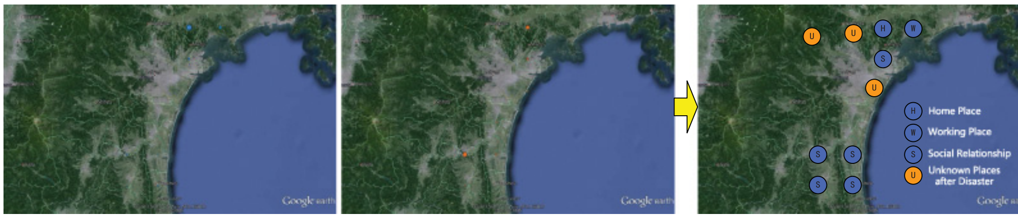


Fig. 5. **Discovery of people's important places before and after the earthquake.[1]** The first two figures show people's geographic location distribution before and after the earthquake. The size of the circles indicates the probability of an individual person staying at a location at a specific time; larger circles indicate higher probability of a person staying or living at a location. Blue and orange circles indicate the distribution before and after the earthquake, respectively. Based on the analysis of this distribution with time, we discover a person's important places (as shown in the third figure).

distribution after the Great East Japan Earthquake and Fukushima nuclear accident in a specific time period, and we discovered some high-frequency staying places to analyze human disaster behavior. Figure 5 shows an example.

Empirical analysis: Based on the seismic scale of the earthquake and the damage level of this composite disaster, we focused on analyzing the population behaviors in the Greater Tokyo Area (the largest metropolitan area in the world with more than one-third the GDP of Japan) and in Fukushima, Miyagi, and Iwate prefectures. In most areas of Fukushima, Miyagi, and Iwate prefectures, the damage level was the highest, and the seismic scale of the earthquake was above five. In contrast, in the Greater Tokyo Area, the damage level was one and the seismic scale was three to four, both of which were relatively low. Although the Greater Tokyo Area did not suffer much damage in this composite disaster, its public transportation systems were completely disrupted (almost the entire metro or railway services). On the other hand, we found that in the first 24 hours after the earthquake, population behaviors or evacuations were mainly in response to the huge earthquake and tsunami themselves. In contrast, during the next several days, the Japanese people understood the seriousness of the Fukushima nuclear accident, prompting large numbers of evacuations or long-distance movements. Therefore, we performed an empirical analysis of the population behavior in two separate time periods.

Figure 6 shows the statistics of various types of human behaviors after the disasters in the Fukushima, Miyagi, and Iwate prefectures and the Greater Tokyo Area, as well as some important news reports related to this event. During the first 24 hours after this disaster, most behaviors of people in the Greater Tokyo Area (Figure 6(a)) were similar to those during normal times; however, at night (8–16 hours after the earthquake), many people had to stay at unknown places (e.g., metro station, hotel, restaurant, etc.) or with their social relations (e.g., friends and colleagues) owing to the disruption of the public transportation systems. In contrast, in most areas of Fukushima, Miyagi, and Iwate prefectures, people chose to stop their work while the earthquake occurred and sought refuge at once at some safe and unknown places (Figure 6(b)) owing to the huge earthquake and tsunami.

On the other hand, during the first 19 days after the earthquake, the majority of people in Fukushima, Miyagi, and Iwate prefectures (Figure 6(d)) chose to leave their home and stopped working owing to the high damage level of this disaster as well as the extensive release of radioactivity. Therefore, they usually went to stay with their social relations or stayed at some unknown places (e.g., government-appointed shelters, hotels in large neighboring cities, etc.). In contrast, the situation in the Greater Tokyo Area was slightly different (Figure 6(c)). Although most areas in the Greater Tokyo Area were not severely damaged, when people began to more fully understand

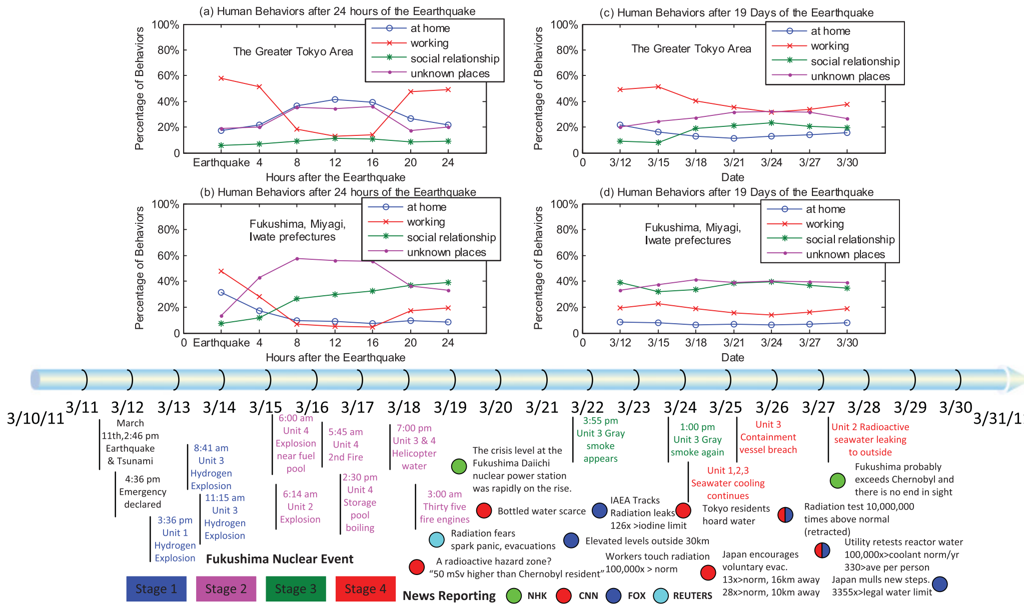


Fig. 6. **Empirical analysis of human behaviors after the Great East Japan Earthquake and Fukushima nuclear accident.** This figure shows the percentage of different human behaviors after this disaster with some important news reports. Figures (a) and (b) show an analysis of human behaviors in the first 24 hours after this disaster in the Greater Tokyo Area and in the Fukushima, Miyagi, and Iwate prefectures. Figures (c) and (d) show the cases during the first 19 days after this disaster.

the seriousness of the Fukushima nuclear accident from the mainstream worldwide media, they stopped working and chose to move far away from East Japan (from 3/15 to 3/27).

4. PREDICTION OF HUMAN DISASTER BEHAVIOR

Based on our empirical analysis of human behavior, we concluded that human behavior and mobility following the Great East Japan Earthquake and Fukushima nuclear accident was sometimes correlated with people's mobility patterns during normal times and was also highly impacted by their social relationships, disaster intensity, damage level, government-appointed shelters, government declarations, news reporting, and so forth. Therefore, in this section, we study and present details regarding how to model human behavior during disasters and how to predict their possible behavior in the next time period.

4.1. Preliminaries

Consider a set of individual people's GPS trajectories $Tra = \{tra_1, tra_2, \ldots, tra_n\}$ after disasters, where each trajectory $tra_i = \mathbf{r}_1\mathbf{r}_2\ldots\mathbf{r}_m$ consists of a series of m GPS records and disaster information. Each record $\mathbf{r}$ is a tuple in the form of $\mathbf{r} = <uid, time, latitude, longtitude, distance, intensity, damage, reporting, behavior>$, where uid is the id of people, $time$ is the time of record, and $latitude$ and $longtitude$ specify the geographic position of the record. $distance$ is the distance from the event (e.g., Fukushima Daiichi nuclear power plant), $intensity$ is the seismic scale of the earthquake at this position, $damage$ is the damage level of this position, and $reporting$ is the government declaration and news reporting level. Here, $behavior$ specifies people's behavior related to the discovered important places before and after the earthquake (as

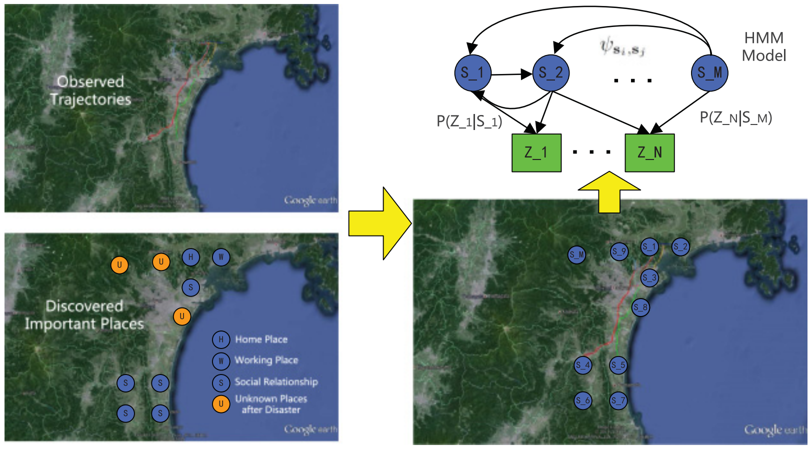


Fig. 7. **HMM-based human behavior model.**[1] Given a person's important places, we use their past movements under various types of disaster states to train an HMM-based human behavior model.

shown in Figure 7), for example, stay at home, work in office, go to important social relationships, evacuate to nearby cities, evacuate to government-appointed shelters, and so forth, and it is a label of discovered important places as described in the previous section.

Therefore, our goal is to learn a prediction model from *Tra*. Given an individual person's GPS trajectory $tra_{ob} = \mathbf{r}_1\mathbf{r}_2\ldots\mathbf{r}_t$ from time 1 to time t, we want to predict their behavior in the next specific time period p at time $t+p$.

4.2. Disaster Behavior Model

HMM-Based behavior model: In this study, we use an HMM [Ye et al. 2013; Zucchini and MacDonald 2009] to model the dependency between disaster behaviors. In our problem, we define a set of hidden states $\mathbf{S} = \{\mathbf{s}_1, \mathbf{s}_2, \ldots, \mathbf{s}_M\}$ that correspond to the human behavior states and a set of observations $\mathbf{Z} = \{\mathbf{z}_1, \mathbf{z}_2, \ldots \mathbf{z}_N\}$ that correspond to the people's GPS records and related disaster states. Figure 6 shows the overall behavior model with its graphical representation. In our study, the following three key parameter components of the HMM need to be learned: (1) initial state probability $\phi_{\mathbf{s}_i}$ for each hidden state $\mathbf{s}_i \in \mathbf{S}$, (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 $P(\mathbf{z}_j|\mathbf{s}_i)$ that determines the probability of the person's mobility $\mathbf{z}_j \in \mathbf{Z}$ given the hidden behavior state $\mathbf{s}_i \in \mathbf{S}$.

We determine people's mobility within a specific time period as a sequence of length T, that is, $tra = \mathbf{Z}_1\mathbf{Z}_2\ldots\mathbf{Z}_T$ (abbreviated as $tra = \mathbf{Z}_{1:T}$), and we use these observed sequences to train the HMM. Here, $\mathbf{Z}_t \in \mathbf{Z}$ represents the observed person's mobility at time t, $1 \le t \le T$. Each $\mathbf{Z}_t$ is associated with a random variable $\mathbf{S}_t \in \mathbf{S}$, representing the unknown behavior state at time t. In the following, we present details of HMM learning.

Model learning: To learn the overall behavior model, we need to estimate the key parameters of HMM as discussed earlier. A suitable solution is to use the EM approach that aims to maximize the likelihood of the observation sequences. In our study, the overall likelihood needs to be summed over all possible routes through the underlying hidden states, and it can be computed as follows:

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

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

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

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

which is expressed by matrix multiplications to reduce the computational cost. Here, Φ is a $1 \times M$ initial state distribution vector, Ψ is an $M \times M$ 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 the Baum-Welch algorithm [Baum et al. 1970] to estimate the state-dependent output probabilities and hidden state transition probabilities.

To decide the correct number of hidden states M in HMM learning, we follow Ye et al. [2013] and use the *Bayesian Information Criterion* (BIC) [Schwarz 1978] to evaluate the model with various state numbers; a smaller value always provides better fitness.

4.3. Prediction of Disaster Behavior

Human mobility within a small time scale will obey higher-order correlation with locations they visited in the past, so we assume this is a Markov process and predict human behavior through Bayesian inference. When given a length-t observed GPS record and its related disaster states $\mathbf{Z}_{1:t}$, we can predict people's behavior $\mathbf{S}_{t+1}$ at time $t+1$ with the learned HMM. This prediction can be achieved by maximizing the probability as follows:

$$\mathbf{S}_{t+1} = \arg\max_{\mathbf{s}_i \in \mathbf{S}} P(\mathbf{S}_{t+1}|\mathbf{Z}_{1:t}), \tag{3}$$

where $P(\mathbf{S}_{t+1}|\mathbf{Z}_{1:t})$ can be computed from the learned $\psi_{\mathbf{s}_t,\mathbf{s}_{t+1}}$ and $P(\mathbf{S}_t|\mathbf{Z}_{1:t})$ according to the law of total probability as follows:

$$P(\mathbf{S}_{t+1}|\mathbf{Z}_{1:t}) = \sum \psi_{\mathbf{s}_t,\mathbf{s}_{t+1}} P(\mathbf{S}_t|\mathbf{Z}_{1:t}), \tag{4}$$

where $P(\mathbf{S}_t|\mathbf{Z}_{1:t})$ can be computed by a Bayesian recursion as follows:

$$P(\mathbf{S}_t|\mathbf{Z}_{1:t}) = \gamma P(\mathbf{Z}_{1:t}|\mathbf{S}_t) \sum \psi_{\mathbf{s}_t,\mathbf{s}_{t-1}} P(\mathbf{S}_{t-1}|\mathbf{Z}_{1:t-1}), \tag{5}$$

where γ is the normalization constant, and $P(\mathbf{Z}_{1:t}|\mathbf{S}_t)$ is the learned observation model of HMM that corresponds to the observed human mobility and disaster states.

To perform efficient behavior prediction, we utilize a particle filter [Doucet et al. 2000] approach to compute Equations (3) through (5). The basic idea behind a particle filter is very simple. Starting with a weighted set of samples $\{w_t^{(k)}, \mathbf{s}_t^{(k)}\}_{k=1}^K$ is approximately distributed according to $p(\mathbf{s}_{t-1}|\mathbf{z}_{t-1})$, and 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

$$w_t^{(k)} \propto w_{t-1}^{(k)} \frac{p(\mathbf{z}_t|\mathbf{s}_t^{(k)})\psi_{\mathbf{s}_t^{(k)},\mathbf{s}_{t-1}^{(k)}}}{q(\mathbf{s}_t^{(k)}|\mathbf{s}_{t-1}^{(k)}, \mathbf{z}_t)}, \sum_{k=1}^{K} w_t^{(k)} = 1. \tag{6}$$

More details on the particle filter technique can be found in Doucet et al. [2000]. In our study, the overall filtering process is as follows:

1. **Initialization:** Generate K weighted set of samples $\{w_t^{(k)}, \mathbf{s}_t^{(k)}\}_{k=1}^K$ from the learned initial state probability $\phi_{\mathbf{s}_i}$ of the HMM.
2. **Resampling:** Resample K particles from the particle set $\mathbf{S}_t$ using the weights of respective particles.

3. **Prediction:** Predict the next state of the particle set $\mathbf{S}_t$ with the learned transition probability $\psi_{\mathbf{s}_i,\mathbf{s}_j}$ of HMM.
4. **Weighting:** Recalculate the weight of $\mathbf{S}_t$ by using Equation (6). Here, we utilize the learned observation model $P(\mathbf{Z}_{1:t}|\mathbf{S}_t)$ of the HMM as the proposed distribution in Equation (6).
5. **State Estimation:** Estimate people's behavior states by calculating the expectation of the particle set $\mathbf{S}_t$.
6. **Iteration:** Iterate Steps 2, 3, 4, and 5 until convergence.

During the particle filtering process, we can easily obtain people's current behavior state $\mathbf{S}_t$ in stage 5 and predict people's behavior $\mathbf{S}_{t+1}$ at the next time period in stage 3.

5. PREDICTION OF HUMAN MOBILITY AFTER DISASTER

Given the predicted behavior of an individual person after the disasters, we also need to predict their possible mobility or evacuation routes, which will play a vital role in effective humanitarian relief and disaster management. In our study, people's predicted behavior usually corresponds to important places, for example, home, working places, parents' or relatives' home, government-appointed shelters, and so forth. Given a predicted place and its current location, it is not difficult to find a possible route for a specific person. *However, a person's mobility following a large-scale disaster is usually different from that under normal circumstances.* During the disaster, a person's mobility will usually be impacted by other people, and they usually tend to find much safer routes for evacuations [Song et al. 2013b]. Furthermore, in most cases, a common transportation network is usually unavailable following large-scale disasters. Therefore, in this section, we present details on how to predict human mobility or their evacuation routes after disasters. Compared to our previous study [Song et al. 2014b, 2015], we consider the transportation mode (e.g., stay, walk, bicycle, car, train) employed by people to construct a mobility graph and predict human mobility following the disaster. Here, the transportation mode is the key information for planning people's traveling routes following the disaster, and it can significantly improve the prediction accuracy.

5.1. Mobility Graph Construction

Given the predicted places where an individual person will go and their current location after the disaster, it is easy to think of using transportation networks to plan and predict their possible movements. However, most public transportation systems are usually not available after an earthquake. Furthermore, based on our previous research, we found that population mobility after large-scale disasters is highly impacted by other people, and sometimes, a large population flow is created [Song et al. 2013a, 2013b, 2014a]. Therefore, modeling large population movements after the disaster will play a vital role in the prediction of an individual person's mobility. In this study, we utilize a large number of population trajectories with transportation mode labels following the Great East Japan Earthquake and Fukushima nuclear accident to construct a population mobility graph to model their mobility through collaborative learning [Wei et al. 2012]. The creation of this type of model is possible because social interactions and political responses in some urban areas are typically stable through time, and large population movements (which are often influenced by these conditions) are likely to remain the same following different emergency situations (e.g., public transportation systems are unavailable again).

To construct the population mobility graph, we first need to discover connected urban areas after the earthquake with the population movements. We divide the geographical range into disjoint cells by a given cell length l. Thus, the specific position of persons can be mapped to a cell, and the overall population trajectories are transformed into a sequence of cells. Then, we computed the connection support of these cells and explored the connected geographical regions. After cell merging, we can build up the region of the population mobility graph. More technical details of this process are available in Wei et al. [2012] and Song et al. [2014a].

Then, we need to infer the edge connections and derive some edge information after region generation, such as travel frequency, travel time, and frequency of different transportation mode. In this study, we follow Wei et al. [2012] and Song et al. [2014a] and use population movements traversing the regions to derive edge connections or information. For each trajectory traversing the regions, the shortest path between any two consecutive points of the trajectory is inferred, and then the travel time of each edge is estimated by the median of all travel times of the edge. In addition, the travel frequency of each edge can be estimated by recording the number of traversing trajectories, and different types of transportation mode are also recorded. Then, we can easily compute the transportation mode possibility in each edge (e.g., stay, walk, bicycle, car, train). Similarly, we can also generate edges between regions: if some trajectories traverse from one region to another, an edge is constructed between the two regions, and its edge information is estimated by the same methods as in previous discussions.

5.2. Urban Mobility Model Learning

Based on the constructed urban mobility graph, the prediction model can be developed using the Markov decision process (MDP) [Puterman 1994]. MDPs provide a natural framework for representing sequential decision making, such as movements through various urban areas. In MDP theory, the agent takes a sequence of *actions* ($a \in A$) that transition between *states* ($s \in S$) and incur an action-based *cost* ($c(a) \in \Re$). The agents try to minimize the sum of costs while reaching some destinations, and the sequence of actions is called a *path* ζ. For MDPs, a set of *features* ($\mathbf{f}_a \in \Re$) characterizes each action, and the cost of the action is the linear function of these features that are parameterized by a *cost weight* vector ($\boldsymbol{\phi} \in \Re$). Path features $\mathbf{f}_\zeta$ are the sum of the features of actions in the path: $\sum_{a\in\zeta} \mathbf{f}_a$. Thus, the cost weight applied to the path features is

$$cost(\zeta|\boldsymbol{\phi}) = \sum_{a\in\zeta} \boldsymbol{\phi}^\top \mathbf{f}_a = \boldsymbol{\phi}^\top \mathbf{f}_\zeta. \tag{7}$$

In our problem, the population mobility graph provides us a deterministic MDP. The urban region (nodes) represents a *state*; the edge, an *action*; and the *path*, people's movements after the earthquake. These movements are parameterized by their path feature $\mathbf{f}_\zeta$. For instance, a person's movements can be described as follows: travel through region A ($dens = 0.37$, $type = residential$) to region B ($dens = 0.58$, $type = commercial$) and finally stay in region C ($dens = 0.75$, $type = administrative$) with route 1 ($frq = 0.37$, $time = 0.58$, $trans = [0.05, 0.12, 0.11, 0.62, 0.10]$) ($A \to B$) and route 2 ($frq = 0.29$, $time = 0.62$, $trans = [0.03, 0.22, 0.08, 0.42, 0.25]$) ($B \to C$), where $dens$ is the region population density; $type$, the region type (e.g., residential, commercial, etc.); frq, the travel frequency of the route; $time$, the travel time of the route; and $trans$, a vector that shows the probability of different transportation modes (stay, walk, bicycle, car, and train). Therefore, we need to utilize all the population trajectories to train an MDP model that can optimally demonstrate these human behaviors after the earthquake. Obviously, this is an *Inverse Reinforcement Learning* problem. In this study, we utilize the *Maximum Entropy Inverse Reinforcement Learning* algorithm [Ziebart et al. 2008] to train the overall predictive model. With this training model, people's movements or behaviors during some future emergency situations can be easily simulated or predicted [Song et al. 2013b, 2014a].

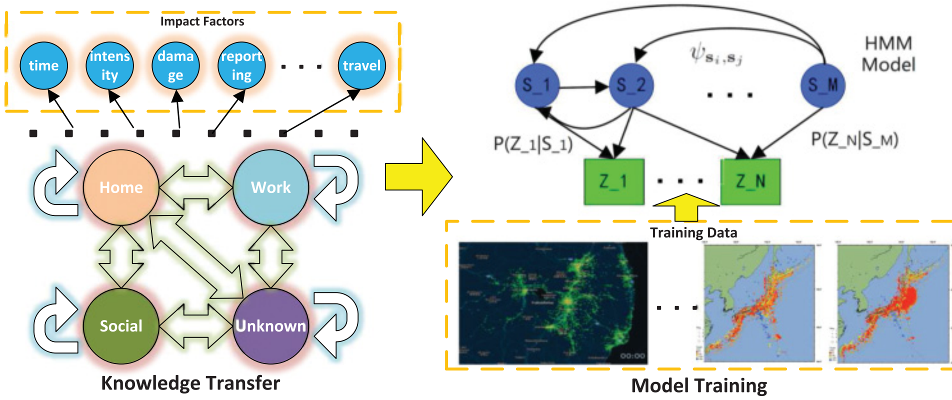


Fig. 8. **Knowledge transfer and model development.** We model human activities and mobility following disasters as random transitions through their home, working location, social relationships, and some unknown places (e.g., shelters or hotels). The transition process will be impacted and influenced by various disaster factors. We develop an HMM-based model and utilize big and heterogeneous data to train its parameters.

5.3. Prediction of Human Mobility

Given the predicted places where an individual person will go, his or her current location after the disaster, and the learned urban mobility models, we can easily predict human movements by performing Markov model route planning. In our study, we assume that people usually try to find a safe, fast, and convenient route (e.g., high-frequency visited route, low travel time, and few transfers) for evacuation after the disaster. Therefore, we employ route planning using the destination-conditioned Markov model [Simmons et al. 2006]. This model recommends the most probable route satisfying the origin and destination constraints. Lastly, we obtain the predicted route for a specific person.

6. KNOWLEDGE TRANSFER AND MOBILITY SIMULATION

Owing to the uniqueness of the Great East Japan Earthquake and Fukushima nuclear accident, our prediction model is difficult to apply to some different disasters (e.g., small-scale ones) and to places not affected by this disaster. Furthermore, the prediction model can only be applied to a specific person for whom historical GPS records are available in the database. Therefore, in this section, we extend our model and try to (1) discover general knowledge from big disaster data and (2) develop a general simulation model for generating or simulating a large amount of human movements following different natural disasters.

6.1. Knowledge Transfer and Simulation Model

Based on previous empirical analysis on human mobility data following disasters, we find that although human behavior and mobility patterns following natural disasters have a high degree of variation and freedom, most mobility is usually based on random movements between a small set of important places, such as home location, working location, social relationships (friends' houses, hometown, etc.), and some unknown places (e.g., shelters, hotels, etc.). Meanwhile, these mobility patterns are also impacted and influenced by various factors (as shown in Figure 8). For instance, if a low-intensity earthquake occurs at midnight, people may stay at home and go back to sleep. In contrast, if a large earthquake occurs at midnight and causes some damage to buildings, people may leave their houses and find some safe places to stay; however, in doing so,

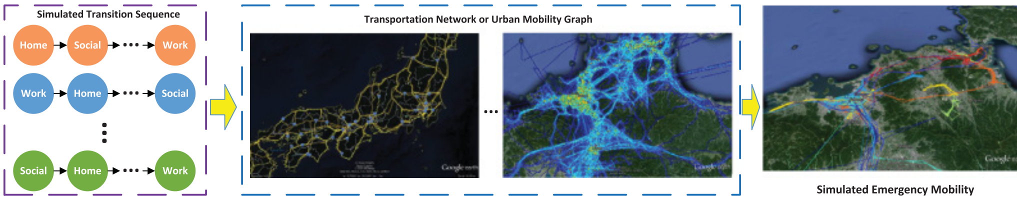


Fig. 9. **Emergency mobility simulation.** Based on our training HMM, we randomly simulate the location transition sequences. Then, we utilize the transportation network or pretrained urban mobility model to plan the traveling routes, and we finally generate human movements following disasters.

they need to consider the travel distance or travel time. Furthermore, if a very large earthquake (such as the 2011 Great East Japan Earthquake) occurs and becomes a composite disaster accompanied with many negative news reports, people may leave the city and find a safe place (e.g., hometown) that is far from the disaster.

Preliminaries: Consider a set of individual people's activities $Activity = \{act_1, act_2, \ldots, act_n\}$ after the disaster, and each activity $act_i = \mathbf{l}_1 \rightarrow \mathbf{l}_2 \rightarrow \cdots \rightarrow \mathbf{l}_m$ denotes a series of m location transfers 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, and $label$ specifies a person'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 earthquake, $intensity$ 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 declaration 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 (e.g., different earthquakes in our disaster information database), we want to randomly simulate or generate people's location transition sequences with the probability.

HMM-based model: Therefore, given a set of disaster information $\mathbf{Y} = \{\mathbf{y}_1, \mathbf{y}_2, \ldots \mathbf{y}_N\}$ such as intensity of earthquake, damage level, news reporting, current time, travel distance, and travel time, we model human activities and mobility following disasters as a random transition through a series of states $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_M\}$, such as home location, working location, social relationship, and some unknown places [Song et al. 2015]. Therefore, we use the HMM as discussed in Section 4.2 to model the dependency between these states, and the overall behavior model with its graphical representation is shown in Figure 8. In this part, we utilize the same training approach as that discussed in Section 4 to train the (1) initial state probability $\phi_{\mathbf{x}_i}$ for each hidden state $\mathbf{x}_i \in \mathbf{X}$, (2) state transition probability $\psi_{\mathbf{x}_i,\mathbf{x}_j}$ from the hidden states $\mathbf{x}_i$ to $\mathbf{x}_j$, and (3) state-dependent output probability $P(\mathbf{y}_j|\mathbf{x}_i)$ that determines the probability of people's mobility $\mathbf{y}_j \in \mathbf{Y}$ given the hidden behavior state $\mathbf{x}_i \in \mathbf{X}$.

6.2. Emergency Mobility Simulation

Given a series of people's important places and disaster information, we aim to randomly simulate and generate their movements following this disaster (as shown in Figure 9). The simulation process mainly has two stages: (1) based on the training HMM behavior model, we randomly generate location transitions through important places; and (2) given the location transition sequences, we use the transportation network or pretrained urban mobility graph discussed in Section 5 to plan the traveling routes. Compared to our previous work [Song et al. 2015], we consider the transportation mode (e.g., stay, walk, bicycle, car, train) of people to plan the traveling routes.

To randomly generate a person's location transition sequence following disasters, we utilize the particle filter [Doucet et al. 2000] approach discussed in Section 4 to simulate this process:

1. **Initialization:** Generate P weighted set of samples $\{w_t^{(k)}, \mathbf{x}_t^{(p)}\}_{p=1}^{P}$ from the learned initial state probability $\phi_{\mathbf{x}_i}$ of our trained HMM.
2. **Resampling:** Resample P particles from the particle set $\mathbf{X}_t$ using the weights of respective particles.
3. **Location Transition Simulation:** Simulate the state transition of the particle set $\mathbf{X}_t$ with the learned transition probability $\psi_{\mathbf{x}_i,\mathbf{x}_j}$ of our trained HMM.
4. **Weighting:** Recalculate the weight of $\mathbf{X}_t$. Here, we utilize the learned observation model $P(\mathbf{Y}_{1:t}|\mathbf{X}_t)$ of our trained HMM as the proposed distribution.
5. **Behavior Selection:** Select a person's transition behavior by finding the highest weight in the particle set $\mathbf{X}_t$.
6. **Iteration:** Iterate Steps 2, 3, 4, and 5 until convergence.

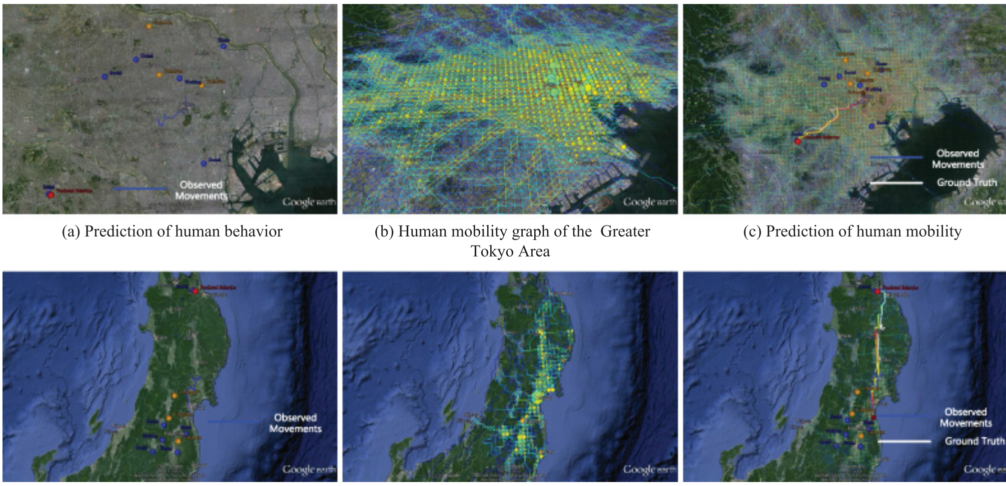
Finally, given the location transition sequences of people following disasters, there are two ways to simulate their traveling routes. For small earthquakes, we can directly use the transportation network (e.g., road network data and metro network) of cities to plan people's traveling routes. Here, we consider the transportation mode of people and use a multimodal route planning approach [Delling et al. 2013; Bast et al. 2013] to compute fast and convenient routes (e.g., low travel time and few transfers). On the other hand, for large-scale earthquakes, public transportation systems are usually unavailable. Therefore, we use the pretrained urban mobility graph as discussed in Section 5 to plan the optimal traveling route (as shown in Figure 9).

7. EXPERIMENTAL RESULTS

In this section, we present extensive experimental results and evaluate our approach for the prediction of human behavior and their mobility.

7.1. Data Preprocessing and Experimental Setup

To evaluate the prediction model, we focused on predicting the population behaviors and their movements in Fukushima, Miyagi, and Iwate prefectures and in the Greater Tokyo Area following the 2011 Great East Japan Earthquake. The three prefectures are the major disaster areas of the Great East Japan Earthquake and Fukushima nuclear accident; the Greater Tokyo Area is the largest metropolitan area in the world and was highly impacted by this event. We selected a person who had more than 3,000 GPS records during the first 20 days after the Great East Japan Earthquake for evaluation, and more than 130,000 persons were analyzed in total. We utilized the GPS records of these persons for several months before this earthquake (August 1, 2010, to March 11, 2011) and for the first 20 days after this earthquake to compute the distribution of geographic locations for individual people and discovered their important places. Meanwhile, we randomly selected 80% of the GPS trajectory segments (with the transportation mode label) for each person after the earthquake to train individual people's behavior models and the urban mobility graph as well as MDP model for entire urban areas. We used the remaining 20% of the data of each person for testing and evaluation. On the other hand, to evaluate the performance of the simulation model (disaster knowledge transfer), we selected human movements (GPS trajectory with the transportation mode label) in 24 hours following different earthquakes from our human mobility database; the selected geotropical regions were places where the earthquake intensity was above one. These GPS trajectories and the related disaster information and disaster reporting information formed the training and testing datasets. We



(a) Prediction of human behavior (b) Human mobility graph of the Greater Tokyo Area (c) Prediction of human mobility

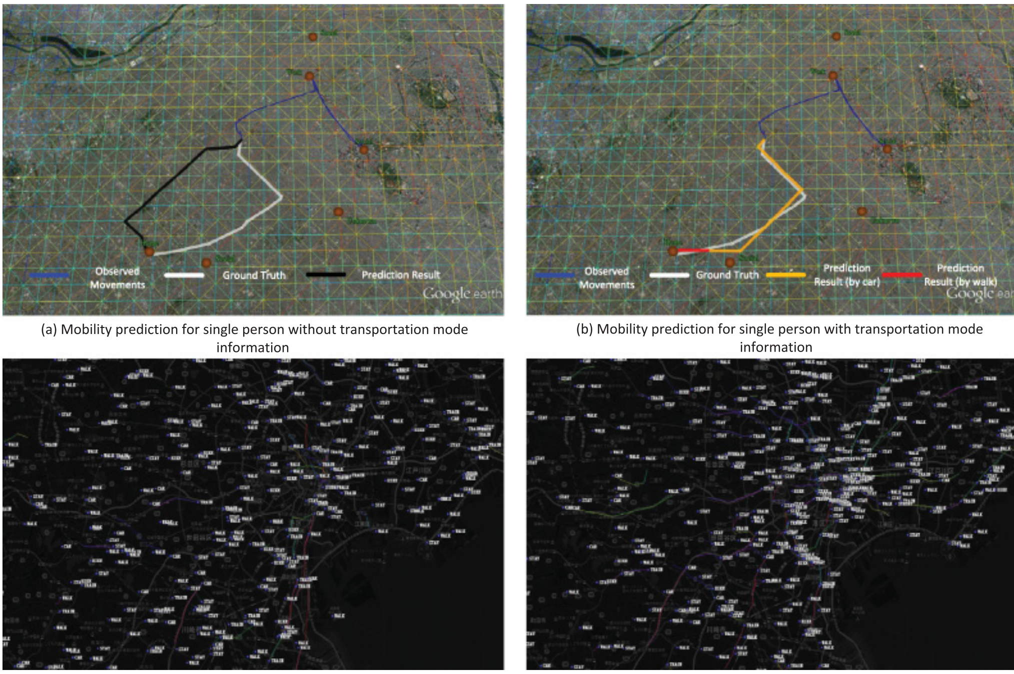
(d) Prediction of human behavior (e) Human mobility graph of Fukushima, Miyagi and Iwate prefectures (f) Prediction of human mobility

Fig. 10. **Visualization of the prediction results without using transportation mode information.**[1] This figure shows our prediction results for human behaviors and their possible movements without using transportation mode information. Given a person's current observed movements (blue lines in Figures (a) and (d)) and their important places (blue and orange circles), the possible destinations are predicted as indicated by red circles (Figures (a) and (d)). Meanwhile, given the learned urban mobility graph (Figures (b) and (e)), a person's possible movements are predicted as indicated by bold and colorful lines (Figures (c) and (f)), and the ground truth is indicated by white lines (Figures (c) and (f)). The first row shows the example results of the person in the Greater Tokyo Area, and our approach predicted his possible movements in the next 4 hours. The second row shows the person's case in Fukushima prefecture, and our model predicted his possible movements in the next 1 day. Note that the edge color in Figures (b) and (e) indicates the edge parameters of the urban human mobility graph. Here, it shows the travel frequency after the earthquake. Warmer colors indicate higher travel frequency, and this value is normalized from 0 to 1. In addition, the color of the predicted trajectories ((c) and (f)) shows the probability as normalized from 0 to 1. The warmer color indicates higher probability.

randomly selected 80% of the data for the model training and used the remaining 20% of the data for testing and evaluation. In the training process, we found that most of the training data were from some very small-scale earthquakes. To balance the training samples of large- and small-scale disasters, we randomly selected 20% of the data from the small-scale disaster set for which the earthquake intensity is below three, and we use them with other disaster data to form a new training sample dataset. We then converted the GPS trajectories in the training set to a sequence of transitions through important places, as discussed in Section 6, to prepare the training samples.

7.2. Visualization of Prediction Results

Figure 10 shows the visualization of our prediction results without using transportation mode information. Given the persons' current observed movements (blue lines) and their important places, our approach predicted the possible destination by the red circle (Figures 10(a) and (d)). Meanwhile, given the learned urban mobility graph (Figures 10(b) and (e)), a person's possible movements were predicted as indicated by bold and colorful lines (Figures 10(c) and (f)), and actual movements are shown by white lines. The first row shows the example results of a person in the Greater Tokyo Area and the predicted possible movements by our approach in the next 4 hours. The second row shows the case of a person in Fukushima prefecture and the predicted possible movements by our model in the next 1 day.



(a) Mobility prediction for single person without transportation mode information

(b) Mobility prediction for single person with transportation mode information

(c) Mobility prediction for multiple persons in Tokyo with transportation mode information

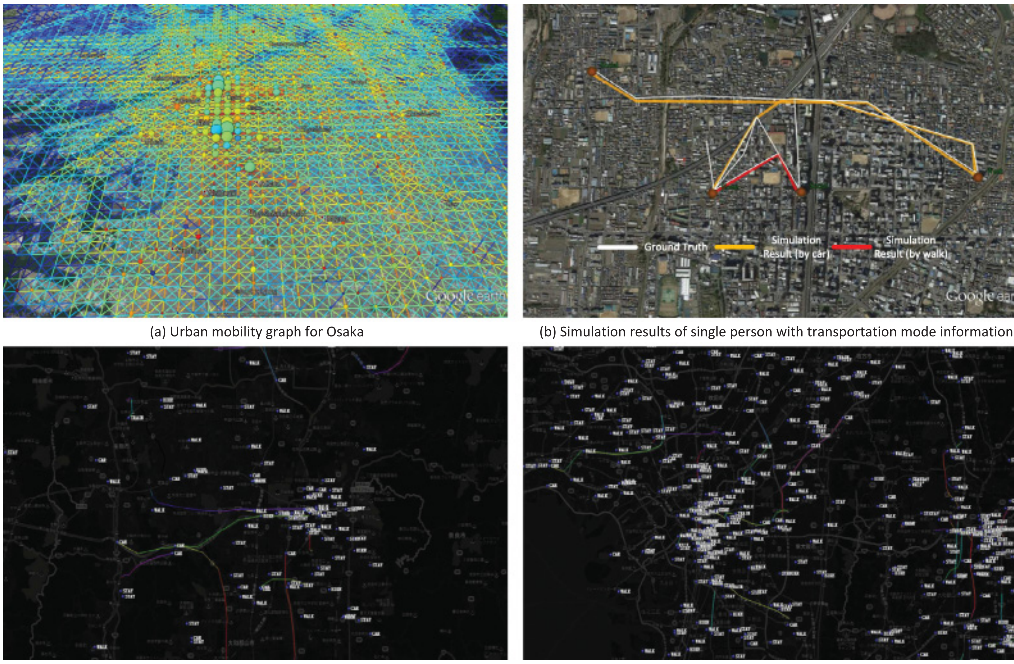
(d) Mobility prediction for multiple persons in Tokyo with transportation mode information

Fig. 11. **Visualization of the mobility prediction results by using transportation mode information.**[1] This figure shows our mobility prediction results by using the transportation mode information. Given the persons' current observed movements (blue lines) and their important places (circles), their mobility and transportation mode were predicted as the colorful lines (e.g., orange line for by car, red line for by walk) as shown in Figure (b). The first row (Figures (a) and (b)) shows the comparison of single-person results between transportation mode information using and nontransportation mode information using. The second row (Figures (c) and (d)) shows the sample results of the multiple-persons case in the Greater Tokyo Area. Here, people's movements of the first 10 minutes were given, and then our model predicted their following movements in the next 30 minutes.

Figure 11 shows the visualization of our mobility prediction results by using the transportation mode information. Given the persons' current observed movements (blue lines) and their important places, their mobility and transportation mode were predicted as the colorful lines (e.g., orange line for by car, red line for by walk) as shown in Figure 11(b). The first row (Figures 11(a) and (b)) shows the comparison of single-person results between transportation mode information using and nontransportation mode information using. From this figure, we can see that the transportation mode information makes the prediction results more reasonable. The second row (Figures 11(c) and (d)) shows the sample results of the multiple-persons case in the Greater Tokyo Area. Here, people's movements of the first 10 minutes were given, and then our model predicted their following movements in the next 30 minutes.

7.3. Visualization of Simulation Results

To simulate human mobility following disasters, users first need to select the important places on the map and then input the disaster information (e.g., occurrence time, earthquake hypocentral location, earthquake intensity at this region, damage level, etc.), and our simulator can then automatically simulate their possible movements and transportation mode. To show the performance, here, we used the real information in



(a) Urban mobility graph for Osaka

(b) Simulation results of single person with transportation mode information

(c) Simulation results of multiple persons in Osaka with transportation mode information

(d) Simulation results of multiple persons in Osaka with transportation mode information

Fig. 12. **Visualization of simulation results.**[1] This figure shows the example of our simulation results for Osaka. Here, we use the pretrained urban mobility model to plan the traveling routes and transportation mode. Figure (a) shows the urban mobility graph of Osaka. Figure (b) shows the example of simulation results for the single person. Figures (c) and (d) show the example of simulation results for a large number of persons in Osaka. Here, the original start positions of people were given, and then we simulated their following movements and transportation mode.

the testing dataset as the input. Figure 12 shows the sample results of our simulator. From Figure 12(b), we can see that our simulation results are very similar to the real movements of this person following a specific disaster. The second row (Figures 12(c) and (d)) shows the sample results of the multiple-persons case in Osaka. Here, the original start positions of people were given, and then we simulated their following movements and transportation mode.

7.4. Evaluation of Behavior Prediction

Evaluation metrics: To evaluate the performance of different predictive models, we followed Cho et al. [2011] and used the following evaluation metrics: (1) Predictive accuracy: This metric measures the overall accuracy of different predictive models; that is, given the time of day of GPS trajectories in the test set, how accurately each model can predict the exact place where the people will go. For instance, an accuracy of 0.7 means that 70% of the time, the model correctly predicts the exact places where people will go. (2) Log-likelihood: This metric measures the average log-likelihood of the GPS trajectories in the test set, which can measure how well the test set fits the model. (3) Expected distance error: This metric does not insist on predicting the exact places. Furthermore, it takes into account the spatial proximity of predictions to the actual destination. For more details and definitions on this metric, please refer to Cho et al. [2011].

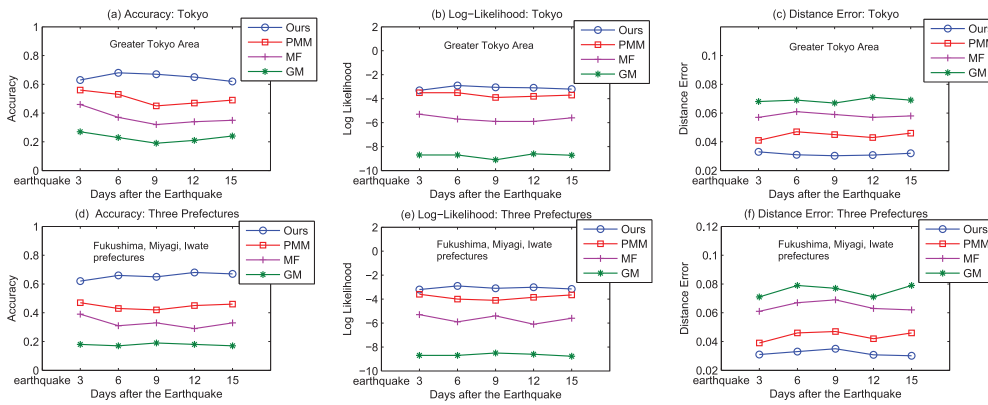


Fig. 13. **Evaluation of behavior prediction.** This figure shows the performance evaluation of four methods with three different evaluation metrics. The first row shows the evaluation of people in the Greater Tokyo Area, and the second row shows the case of people in Fukushima, Miyagi, and Iwate prefectures.

Baseline models: We considered three baseline models for comparison: (1) *Most Frequented Location Model (MF):* For every hour of the day, this model predicts the most likely (most frequently visited) place for a particular person. Despite its simplicity, this is a strong baseline model. Lu et al. [2012] also used this model to predict population mobility after the 2010 Haitian earthquake. (2) *Gaussian Model (GM):* This model has been proposed by Gonzalez et al. [2008], and it models human movements as a stochastic process centered around a single point. This model is static in time and mainly captures the scale of a person's movements. (3) *Periodic Mobility Model (PMM):* This model is built on the intuition that most human mobility is based on periodic movement among a small set of locations. As a state-of-the-art method, it has been proposed by Cho et al. [2011] to predict the locations and dynamics of future human movements.

Performance evaluation: We compared the performance of our model with that of the baselines, as shown in Figure 13. From this figure, we can see that our approach achieved much better performance than the other competing methods in our dataset. In addition, we can see that on the first 3 days after the earthquake, the performance of PMM for people in the Greater Tokyo Area is similar to that of our approach (Figure 13(a)); however, our method outperforms PMM considerably at other times. This might be because on the first 3 days after the earthquake, many people's mobility in the Greater Tokyo Area was the same as their mobility during normal times (e.g., working at daytime and going home at night). However, on the following days, people began to more fully understand the seriousness of the Fukushima nuclear accident, and many of them chose to evacuate to other places. Obviously, our approach is powerful for predicting human disaster behaviors and emergency mobility than these competing methods that are used for predicting human mobility during normal times.

7.5. Evaluation of Mobility Prediction

To evaluate the accuracy of the predictive paths of people, we used the three different metrics discussed in Ziebart et al. [2008]. The first evaluates the amount of route distance shared between the model's most likely path estimate and the actual demonstrated path. The second measures what percentage of the testing paths match at least 90% (distance) with the predicted one. The third evaluates the average log probability of paths in the training set under the given model. Meanwhile, we chose the approach developed by Song et al. [2014a] as the first baseline model. This approach also uses the

Table I. Evaluation of Mobility Prediction

Algorithm	Matching	90% Matching	Log-Prob
Our method (transportation mode using) (Greater Tokyo Area)	82.75%	61.69%	−6.17
Method of Song et al. [2014b] (Greater Tokyo Area)	80.68%	58.73%	−6.53
Method of Song et al. [2014a] (Greater Tokyo Area)	72.76%	51.27%	−7.15
Our method (transportation mode using) (other three prefectures)	86.22%	67.38%	−5.31
Method of Song et al. [2014b] (other three prefectures)	83.39%	63.36%	−5.97
Method of Song et al. [2014a] (other three prefectures)	73.28%	52.28%	−7.33

Table II. Evaluation of Simulation Accuracy

Algorithm	Matching	90% Matching	Log-Prob
Our model (transportation mode using)	69.52%	49.31%	−6.72
Model of Song et al. [2015] (nontransportation mode)	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

population mobility graph to predict possible population movements after a large-scale disaster; however, it does not take into account the important places of people and some important disaster states. On the other hand, we chose the previous version of our model [Song et al. 2014b], which did not consider transportation mode information, as the second baseline model.

Table I shows the performance of the three models. We can see that our method outperforms the method proposed by Song et al. [2014a] by 9.99% to 15.10%. In addition, we can see that the transportation mode information improves the mobility prediction accuracy, and it outperforms our previous models [Song et al. 2014b] by 2.07% to 4.02%.

7.6. Evaluation of Simulation Accuracy

To evaluate the accuracy of the simulation model, we used the same metrics as those discussed in Section 7.5: *distance match*, *90% match*, and *average log probability*. Meanwhile, we considered the same baseline models as those discussed in Section 7.4 for comparison: *Most Frequented Location Model (MF)*, *Gaussian Model (GM)*, *Periodic Mobility Model (PMM)*, and our previous model [Song et al. 2015] that did not consider transportation mode information. For training these baseline models, we retrieved the GPS data in 3 months from our mobility database by using the person ID in the testing set, and we used them to train the final model. Then, we used these baseline models to predict a person's next visited place following the disaster, and then we planned the final traveling routes of people in the transportation network.

We compared the performance of our model with those of the baselines, as shown in Table II. Most of the baseline models (e.g., MF, GM, and PMM) are trained by a particular person's historical movements, and they can only be applied to a specific person. In contrast, our model is a general mobility model, and it can be applied to any person. From this table, we can see that our model has much better performance than MF, GM, and PMM. Obviously, our simulator is more powerful for simulating human mobility during disasters than these competing methods that are used for predicting or simulating human mobility during normal times. In addition, compared to the previous version of our approach [Song et al. 2015], the transportation mode information and multimodal route planning significantly improve the simulation accuracy.

8. CONCLUSION

In this article, we collect big and heterogeneous data to capture and analyze human mobility following different disasters in Japan, and we develop a model of human mobility for predicting and simulating human movements following natural disasters. The experimental results and validations demonstrate the efficiency of our behavior model and suggest that human mobility following natural disasters may be more easily predicted or simulated than previously thought.

We note several limitations within our study. The population mobility database used is constructed from mobile devices and does not incorporate data from some representative portions of the population (i.e., people who do not own mobile devices or do not register for a GPS service cannot be incorporated into this study). Additionally, the data are slightly biased toward younger age groups, who are more likely to own GPS-based equipment than older age groups. However, we are confident that the data, which offers movement behaviors for the approximately 1.6 million people included in the database, are reflective of general movement patterns in the country following a composite disaster. A second limitation of our study is related to the training process. 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 a Deep Belief Net and utilize deep learning technology to model a large number of human emergency movements.

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