Prediction of Human Emergency Behavior and their Mobility following Large-scale Disaster

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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, accurately predicting human emergency behavior and their mobility will become the critical issue for planning effective humanitarian relief, disaster management, and long-term societal reconstruction. In this paper, we build up a large human mobility database (GPS records of 1.6 million users over one year) and several different datasets to capture and analyze human emergency behavior and their mobility following the Great East Japan Earthquake and Fukushima nuclear accident. Based on our empirical analysis through these data, we find that human behavior and their mobility following large-scale disaster sometimes correlate with their mobility patterns during normal times, and are also highly impacted by their social relationship, intensity of disaster, damage level, government appointed shelters, news reporting, large population flow and etc. On the basis of these findings, we develop a model of human behavior that takes into account these factors for accurately predicting human emergency behavior and their mobility following large-scale disaster. The experimental results and validations demonstrate the efficiency of our behavior model, and suggest that human behavior and their movements during disasters may be significantly more predictable than previously thought.

Categories and Subject Descriptors

H.2 [**Database Management**]: Spatial databases and GIS; H.2 [**Database Management**]: Data mining; H.4 [**Information Systems Applications**]: Decision support (e.g., MIS)

Keywords

human mobility, disaster informatics, spatio-temporal data mining

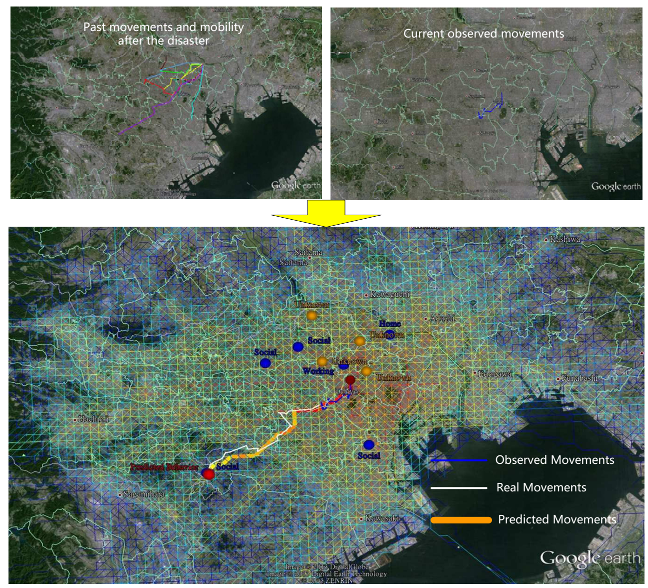

Figure 1: Prediction of human emergency behavior and their mobility following large-scale disaster. Can we predict human emergency behavior and its movements by modeling its past movements during disaster? If some future disaster occur, given person's current observed movements, which place will it go next time period? How about its traveling routes?

1. INTRODUCTION

Most severe disasters cause large population movements and evacuations. Predicting these movements are critical for planning effective humanitarian relief, disaster management, and long-term societal reconstruction. 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 [1]. In particular, after large-scale disasters, population mobility pattern seem to be highly influenced by several disaster states and various factors, such as intensity of disaster, damage level, government declarations, news reports and etc [2]. Lu *et al.* [3] found that population mobility patterns following the 2010 Haitian earthquake disaster were highly correlated with their daily movements prior to the event, and concluded that population movements after large-scale disasters may be significantly more predictable than previously thought. Song *et al.* [2] 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 more impacted by the release of nuclear materials, evacuation patterns were highly influenced by government declarations and news reports.

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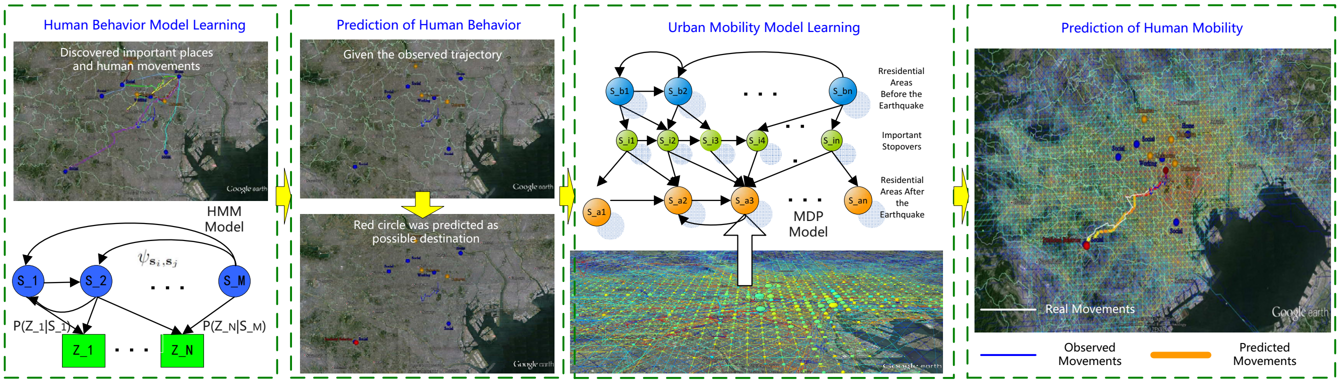


Figure 2: Overview of the approach. Our approach decomposes the predicting problem into two sub-problems: (1) Firstly, we use people's past movements during disasters, and its important places to train a HMM-based human behavior model. Then, given person's current observed movements and disaster states, our model predicts its possible behavior at next time period. (2) Secondly, we use the whole collected population movements of a specific urban areas to train the urban mobility model. Then, our model predicts person's possible movements given its predicted behavior at next time period.

Even though the above are some of the fundamental questions and hypotheses about human behavior and mobility after large-scale disasters, answers to them remain largely unknown mostly due to the lack of supported data or a powerful human behavior model that is able to fully depict how these factors will influence population mobility patterns. Therefore, in this paper, we built up a large population mobility database that stored and managed daily GPS records from approximately 1.6 million individuals throughout Japan over one year (from 1 August 2010 to 31 July 2011), and several different dataset to capture and analyze population behavior and their mobility following the Great East Japan Earthquake and Fukushima nuclear accident. On the basis of empirical analysis of population mobility patterns through these databases, we found that population behavior and their mobility after this unprecedented composite disaster sometimes correlated with their mobility patterns during normal times, and were also highly impacted by their social relationship, intensity of disaster, damage level, government appointed shelters, government declarations, movements of large population flow and etc (as shown in Figure 1). Based on these findings, we tried to model the relationship between human emergency behavior and these influenced factors, and developed a model of human behavior for predicting population movements following large-scale disaster. In our work, we decomposed the predicting problem into two sub-problems (as illustrated in Figure 2): (1) given the current state of disasters or other influenced factors, and observed human movements, predicting its possible behavior at next step; and then (2) predicting its possible movements given the estimated behavior distribution. *To the best of our knowledge, this work is the first to model human emergency behavior under various disaster states, and is able to accurately predict population movements following large-scale disasters.*

The remainder of this paper is structured as follows: Section 2 introduces the databases and the empirical analysis of population mobility patterns following the Great East Japan Earthquake and Fukushima nuclear accident. Section 3 describes the human behavior model based on our empirical analysis, and the prediction of human behavior after disasters. Section 4 provides the details about urban mobility model learning, and the prediction of human movements. Experimental results are presented in Section 5. Related work is briefly reviewed in Section 6, and the paper is finally summarized in Section 7.

2. DATABASE AND EMPIRICAL ANALYSIS

2.1 Database

In this study, we built up a large human mobility database and several different dataset to capture and analyze population emergency behavior and their mobility following large-scale disaster, and they were able to be summarized as follows:

Human mobility database: This mobility database stored and managed GPS records of approximately 1.6 million anonymized users throughout Japan from 1 August 2010 to 31 July 2011, which contained approximately 9.2 billion GPS records, more than 600GB csv files. We utilized five computer (Xeon 2.6GHz CPU, 8GB memory, and 2x2TB disk.) 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. Furthermore, we utilized Hive on top of Hadoop to make the whole system support SQL-like spatial query. The visualization of human mobility in the Greater Tokyo Area during the earthquake is shown in Figure 3. From this figure, we can clearly see that the transportation of Tokyo before the earthquake was very busy (Fig.3-A,B). In contrast, after the earthquake, the transportation network of whole Greater Tokyo Area was almost stalled (Fig.3-C,D).

Disaster intensity data: We collected various kinds of disaster information about the Great East Japan Earthquake and Fukushima nuclear accident from Japan Government statistical reports, and built up a disaster intensity dataset. This dataset contained seismic scale of the earthquake and damage level (1-4) of this composite disaster (e.g. destroyed buildings by the earthquake and tsunami) in the whole East Japan.

Disaster reporting data: Serious radioactive releases (e.g. Fuku shima Daiichi nuclear accident) were quite different from the traditional natural diaster, because its real affection was still uncertain to human society, and will last for a very long time [2]. Facing such kind of unfamiliar disaster, people did not have direct feeling of its destructiveness, and their mobility were usually influenced and caused by government declarations or various kinds of news reporting [2]. To capture this influence, we collected government declarations [4] as well as news reports from mainstream medias in Japan and all over the world [5] from 11th March, 15:00 to 31 March, 24:00, and built up a disaster reporting dataset. Based on these information, we empirically divided these reporting and dec-

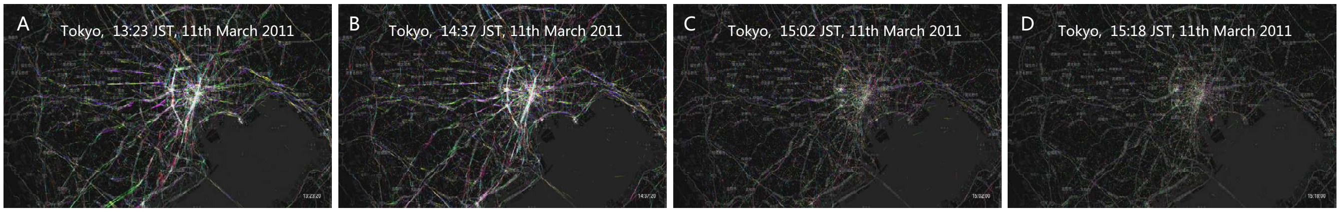
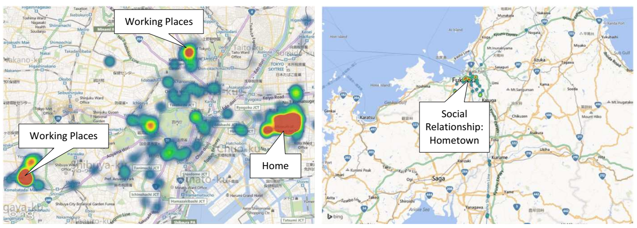


Figure 3: Visualization of human mobility during the earthquake. This figure shows population mobility of the Greater Tokyo Area during the earthquake. The color denotes the directions of population mobility. Figure A and B show population mobility before the earthquake, and Figure C and D show the ones after the earthquake. We can clearly see that the whole transportation of the Greater Tokyo Area was stopped suddenly during the earthquake (Fig.C,D). For more details, please see our supplementary video.



(a) Distribution of geographic location on woking days

(b) Distribution of geographic location on important holidays

Figure 4: Distribution of geographic location for individual people. This figure shows the distribution of geographic location for specific person (one of the authors) during normal times. The color denotes the probability of staying location of an individual 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).

larations into four levels to measure this event (e.g. one level means not serious from the reporting, and four level means extremely serious), and performed the time series analysis.

2.2 Empirical Analysis of Human Disaster Behavior

Important places discovery: While people travel further and faster than ever before, it is still the case that they spend much of their time at a few important places. To perform the analysis of population emergency behavior, we need to discover and recognize important places in people's lives, e.g. home, working places, and places of important social relationships (e.g. hometown, parents, relatives and good friends). In this study, we utilized GPS data in several months before the earthquake (1st, August 2010 to 11st, March 2011) to compute distribution of geographic location [2, 6] 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 of individual people. For example, the highest frequency staying place by daylight on working day is usually people's working place, and the one in night is usually people's home (as shown in Figure 4-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 people's important social relationships (as shown in Figure 4-b). Furthermore, we also computed people's geographic location distribution after the Great East Japan Earthquake and Fukushima nuclear accident in a specific time period, and discover some high frequency staying places to analyze human disaster behavior. The example is shown in Figure 5.

Empirical Analysis: On the basis of seismic scale of the earthquake and damage level of this composite disaster, we focused on analyzing population behaviors in Fukushima, Miyagi, Iwate prefectures and the Greater Tokyo Area (the largest metropolitan area in the world with more than 1/3 GDP of Japan). In most areas of Fukushima, Miyagi, Iwate prefectures, the damage level were the highest ones, and seismic scale of the earthquake were above five. In contrast, the damage level and seismic scale of the Greater Tokyo Area were relatively low, most of which were with one damage level, three to four seismic scale. Although the Greater Tokyo Area were not highly destroyed by this composite disaster, its public transportation systems were completely disrupted (almost the whole metro or railway services). On the other hand, we found that: on the first 24 hours after the earthquake, population behaviors or evacuations were mainly responded to the huge earthquake and tsunami themselves. In contrast, on the next several days, Japan people understood the seriousness of the Fukushima nuclear accident, and large number of evacuations or long distance movements were discovered. Hence, we performed the empirical analysis of population behavior in the two separated time periods.

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

On the other hand, during the 19 days after the earthquake, the majority of people in Fukushima, Miyagi, Iwate prefectures (Fig.6-d) chose to leave their home and stop working due to the high damage level of this disaster as well as extensive release of radioactivity, they usually went to stay with their social relationship or stayed at some unknown places (e.g. government appointed shelters, hotels of large neighboring cities and etc.). In contrast, the situation of the Greater Tokyo Area was a bit different (Fig.6-c). Although most areas in the Greater Tokyo Area were not severely damaged, when people began to more fully understand the seriousness of the Fukushima nuclear accident from the mainstream worldwide media, they stopped working and chose to leave far away from the East Japan (from 3/15 to 3/27).

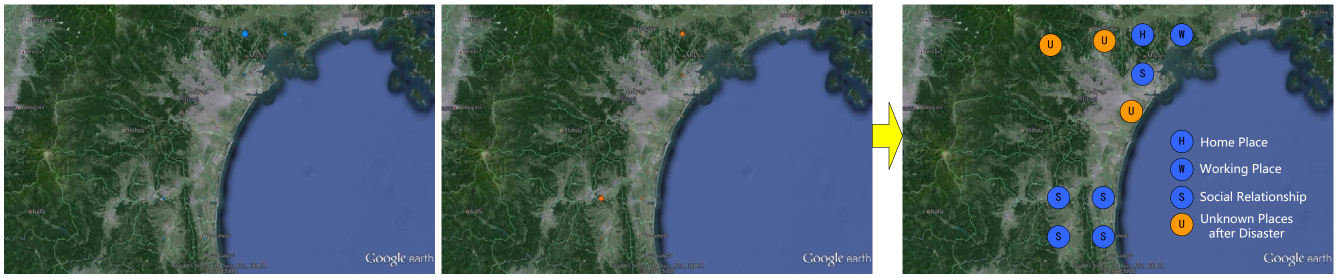


Figure 5: Discovery of people's important places before and after the earthquake. The first two figures show people's geographic location distribution before and after the earthquake. The size of the circles indicates the probability of staying location of an individual person at a specific time; larger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

3. PREDICTION OF HUMAN DISASTER BEHAVIOR

Based on our empirical analysis of human behavior above, we concluded that human emergency behavior and mobility following the Great East Japan Earthquake and Fukushima nuclear accident sometimes correlated with their mobility patterns during normal times, and were also highly impacted by their social relationship, intensity of disaster, damage level, government appointed shelters, government declarations, news reporting and etc. Hence, in this section, we study how to model human disaster behavior by considering these influenced factors, and predict their possible behavior at next time period.

3.1 Preliminaries

Consider a set of individual people's GPS trajectories $Tra = \{tra_1, tra_2, ..., tra_n\}$ after the disasters, and each trajectories $tra_i = \mathbf{r}_1\mathbf{r}_2...\mathbf{r}_m$ 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, $latitude$ 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 declarations and news reporting level. Here, $behavior$ specify the people's behavior related to the discovered important places before and after the earthquake (as shown in Figure 5), e.g., stay at home, work in office, go to important social relationships, evacuate to nearby cities, evacuate to government appointed shelters, etc., and it is a label of discovered important places as described in the last section.

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

3.2 Disaster Behavior Model

HMM based Behavior Model: In this study, we use hidden Markov model (HMM) [7, 8] to model dependency between disaster behaviors. In our problem, we define a set of hidden states $\mathbf{S} = \{\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_M\}$ which correspond to the human behavior states, and a set of observations $\mathbf{Z} = \{\mathbf{z}_1, \mathbf{z}_2, ...\mathbf{z}_N\}$ which correspond to the people's GPS records and its related disaster states. The overall behavior model with its graphical representation is shown in Figure 7. 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 $\mathbf{s}_i \in \mathbf{S}$.

We abstract people's mobility within a specific time period as a sequence of length T, i.e., $tra = \mathbf{Z}_1\mathbf{Z}_2...\mathbf{Z}_T$ (abbreviated as $tra = \mathbf{Z}_{1:T}$), and use these observed sequences to train the HMM. Here, $\mathbf{Z}_t \in \mathbf{Z}$ represents the observed people'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 will present details on HMM model learning.

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 observation sequences. In our study, the overall likelihood should be summed over all possible routes through the underlying hidden states, and is able to be computed by:

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

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 [8], we reformulate Equation (1) as:

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

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 [9] 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) [10] to evaluate the HMM with different state numbers, and a smaller BIC value always leads to better model fitness.

3.3 Prediction of Disaster Behavior

When given a length-t observed GPS records 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 learnt HMM. This prediction is able to be achieved

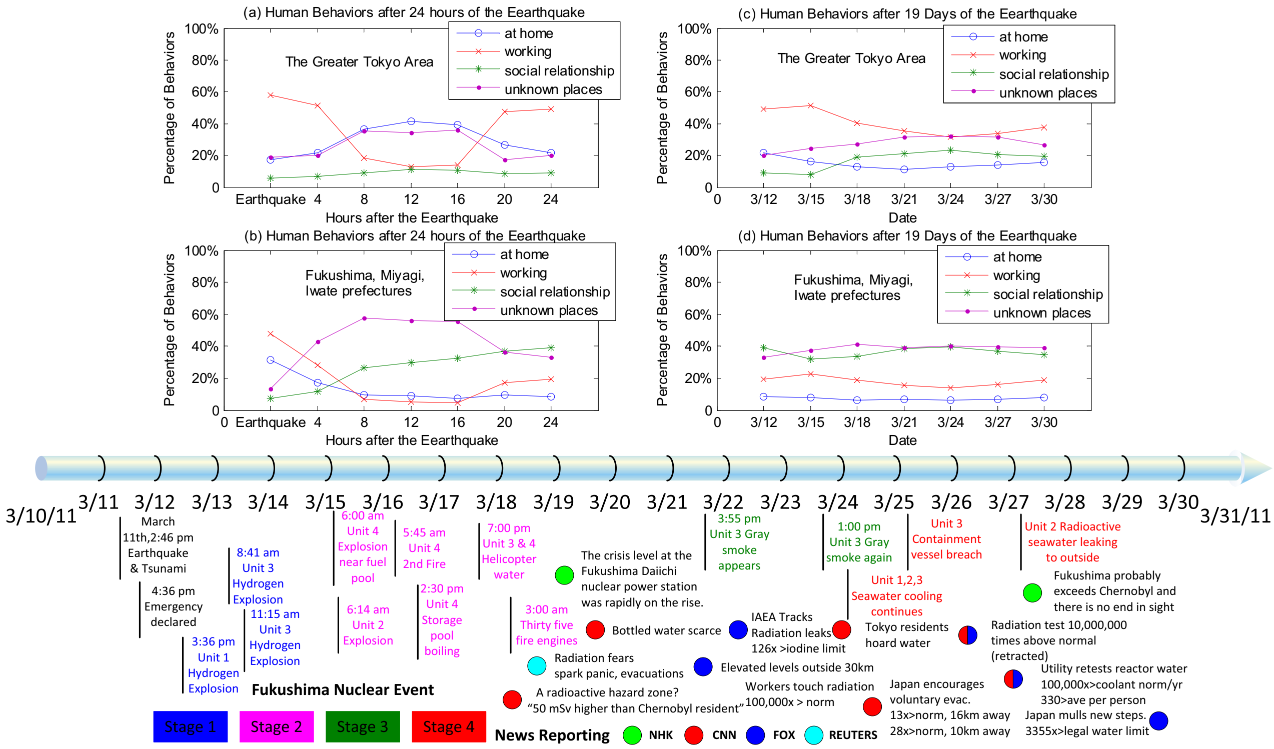


Figure 6: Empirical analysis of human behaviors after the Great East Japan Earthquake and Fukushima nuclear accident. This figure shows percentage of different human behaviors after this disaster with some important news reporting. Figure (a) and (b) show analysis of human behaviors at first 24 hours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

by maximizing the probability as:

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

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

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

where $P(\mathbf{S}_t|\mathbf{Z}_{1:t})$ is able to be computed by a Bayesian recursion:

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

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

To perform the efficient behavior prediction, we utilize particle filter [11] approach to compute Equation (3)-(5). The basic idea behind a particle filter is very simple. Starting with a weighted set of samples $\{w_t^{(k)}, \mathbf{s}_t^{(k)}\}_{k=1}^K$ 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

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

More details on the particle filter technique can be found in [11]. In our study, the overall filtering 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 HMM.

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

3. Prediction:
Predict the next state of the particle set $\mathbf{S}_t$ with the learnt 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 learnt observation model $P(\mathbf{Z}_{1:t}|\mathbf{S}_t)$ of HMM as the proposal distribution in Equation (6).

5. States 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 next time period in stage 3.

4. PREDICTION OF HUMAN MOBILITY AFTER DISASTER

Given the predicted behavior of individual person after the disasters, we also need to predict its possible mobility or evacuation routes, which will play a vital role on effective humanitarian relief and disaster management. In our study, people's predicted behavior is usually corresponding to an important places, e.g., home, work-

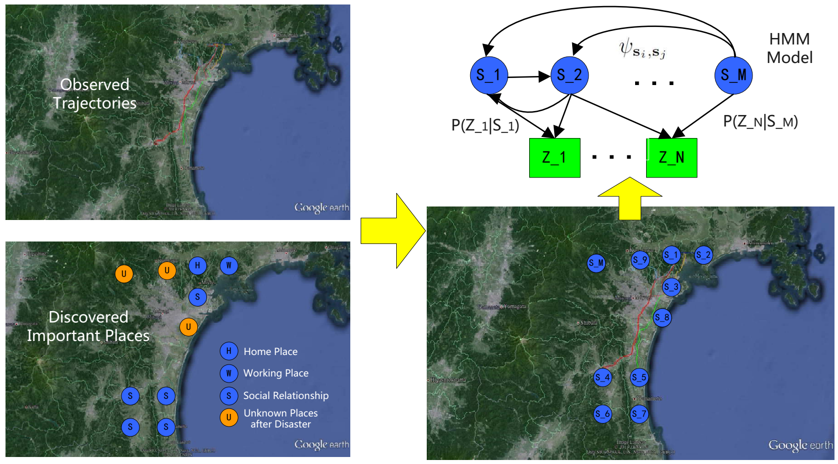


Figure 7: HMM-based human behavior model. Given person's important places, we use its past movements under various kinds of diaster states to train a HMM-based human behavior model.

ing places, parents or relatives' home, government appointed shelters and etc., given a predicted place and its current location, it is not difficult to find a possible route for a specific person. *However, human's mobility following large-scale disaster is usually different from the ones under normal circumstances.* During the disaster, human's mobility usually will be impacted by other people, and they usually tend to find a much safer routes for evacuations [2]. Furthermore, in most cases, the common transportation network is usually unavailable following large-scale disasters (as shown in Figure 3). Hence, in this section, we will present details on how to predict human mobility or their evacuation routes after disasters.

4.1 Mobility Graph Construction

Given the predicted places where individual person will go and its current location after the disasters, it is easy to think of using transportation networks to plan and predict its possible movements. However, most public transportation systems are usually not available after the earthquake occurred. Furthermore, based on our previous research, we found that population mobility after large-scale disaster would highly impacted by other people, and sometimes became a large population flow [2, 12, 13, 15]. Therefore, modeling large population movements after the disasters will play a vital role on prediction of individual person's mobility. In this study, we utilize a large number of population trajectories following the Great East Japan Earthquake and Fukushima nuclear accident to construct population mobility graph to model their mobility through collaborative learning [14]. 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. the public transportation systems are unavailable again).

Region Construction: To construct the population mobility graph, we firstly need to discover connected urban areas after earthquake with the population movements. We divide the geographical range into disjoint cells by a given cell length l. Thus, the specific position of the persons is able to be mapped into a cell, and overall population trajectories are transformed into a sequence of cells. Then, we computed connection support of these cells, and explored the connected geographical regions. After cell merging process, we can build up the region of the population mobility graph. For more technical detail about it, please refer [14, 15].

Edge Inference: Once the regions in the population mobility graph are generated, we then need to infer edges and derive some edge information, such as travel frequency, travel time and etc. In this study, the mobility graph is a directed graph $G = (V, E)$, where V is a set of vertices and E is a set of edges. Each vertex v represents a geographical area, and the directed edge e indicates a transition relationship, including travel frequency and travel time.

Given the constructed regions R, and the population trajectories, we utilize these population movements traversing the regions to derive edge connections and information within regions. For each trajectory traversing the region, we infer the shortest path between any two consecutive points of the trajectory by virtual bidirected edges in the region, and the travel time of each edge is estimated by the median of all the travel times of the edge. In addition, the travel frequency of each edge is able to be estimated by recording the number of traversing trajectories. Similarly, we can also generate edges between regions: if some trajectories traversers from one region to another region, the edges is constructed between the two regions, and its edge information is estimated by the same methods as previous discussions.

4.2 Urban Mobility Model Learning

Based on the constructed urban mobility graph, the prediction model is able to be developed by using the Markov Decision Process (MDPs) [16]. MDPs provide a natural framework for representing sequential decision making, such as movements through various of urban areas. In MDP theory, the agent takes as sequence of *actions* ($a \in A$), which transition between *states* ($s \in S$) and incur and action-based *cost* ($c(a) \in \Re$). The agent is trying to minimize the sum of costs while reaching some destination, and the sequence of action is called a *path* ζ. For MDPs, a set of *features* ($\mathbf{f}_a \in \Re$) characterize each action, and the cost of the action is a linear function of these features parameterized by a *cost weight* vector ($\boldsymbol{\phi} \in \Re$). Path feature, $\mathbf{f}_\zeta$ 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 provide us a deterministic MDP, the urban region (nodes) is able to be seem as *state*, the edge is the *action*, and the *path* is the 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 by: travel through region A ($dens = 0.37$, $type = residential$) to region B ($dens = 0.58$, $type = commercial$), and finally stayed in region 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, and etc. Hence, we need to utilize all the population trajectories to train a MDPs model that is able to optimally demonstrate these people's behavior after the earthquake. Obviously, this is an *Inverse Reinforcement Learning* problem. In this study, we utilize the *Maximum Entropy Inverse Reinforcement Learning* algorithm [17, 18] to train the overall predictive model. With this training model, the people's movement or behaviors during some future emergency situations is able to be easily simulated or predicted [2, 15].

4.3 Prediction of Human Mobility

Given the predicted places where individual person will go, its current location after the disasters and the learnt urban mobility models, we can easily predict human movements 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 after the disasters. Hence, we employ the route planning using the destination-conditioned Markov Model [19]. This model recommends the most probable route satisfying origin and destination constraints. Lastly, we can obtain predicted route for a specific person (as shown in Figure 8-c,f).

5. EXPERIMENTAL RESULTS

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

5.1 Data Pre-processing and Experimental Setup

In our experiments, we focused on predicting population behaviors and their movements in Fukushima, Miyagi, Iwate prefectures and the Greater Tokyo Area. The three prefectures are the major disaster areas of the Great East Japan Earthquake and Fukushima nuclear accident, and the Greater Tokyo Area is the largest metropolitan area in the world which is as well highly impacted by this event. We selected the person who had more than 3,000 GPS records during 20 days after the earthquake for evaluation, and the total number of analyzed persons was more than 130,000. We utilized the GPS records of these persons in several months before the earthquake (1st, August 2010 to 11st, March 2011) and 20 days data after the earthquake to compute distribution of geographic location for individual people, and discovered their important places. Meanwhile, we randomly selected 80% of their GPS trajectories after the earthquake to train the behavior model for individual people, and the urban mobility graph as well as MDP model for the whole urban areas. We used the remaining 20% data for testing and evaluation.

5.2 Visualization of Results

Figure 8 shows the visualization of our prediction results. Given the persons' current observed movements (blue lines), and its important places, our approach predicted its possible destination as the red circle (Fig.8-a,d). Meanwhile, given the learnt urban mobility graph (Fig.8-b,e), persons' possible movements were predicted as the bold and colorful lines (Fig.8-c,f), and its actual movements were shown in the white lines. The first row shows the example results of a person in the Greater Tokyo Area, our approach predicted its possible movements at next four hours. The second row shows the person's case in Fukushima prefecture, and our model predicted its possible movements at next one day.

5.3 Evaluation of Behavior Prediction

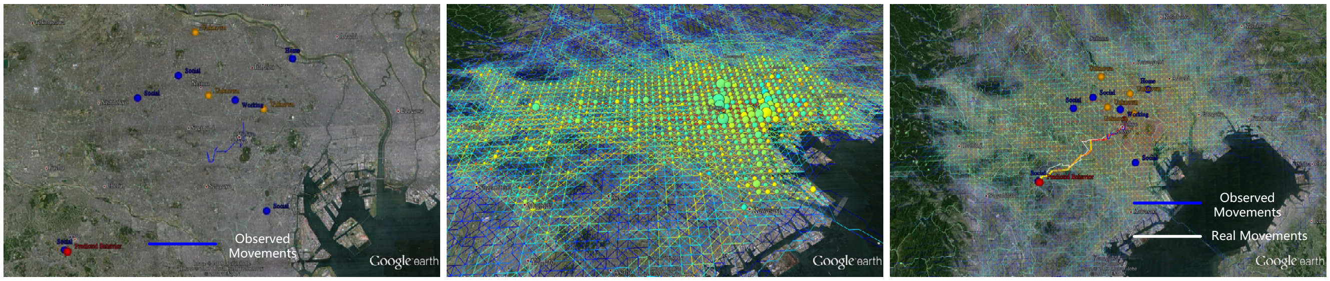
Evaluation metrics: To evaluate the performance of different predictive model, we followed the work [1], and used the following evaluation metrics. (1) Predictive accuracy: This metric measures the overall accuracy of different predictive models, i.e., given the time of day of GPS trajectories in the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

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 predicts the most likely (most frequent visited) place of a particular people. Despite its simplicity, this model is very strong baseline. Lu *et al.* [3] 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.* [20], 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.* [1], which is able to predict the locations and dynamics of future human movements.

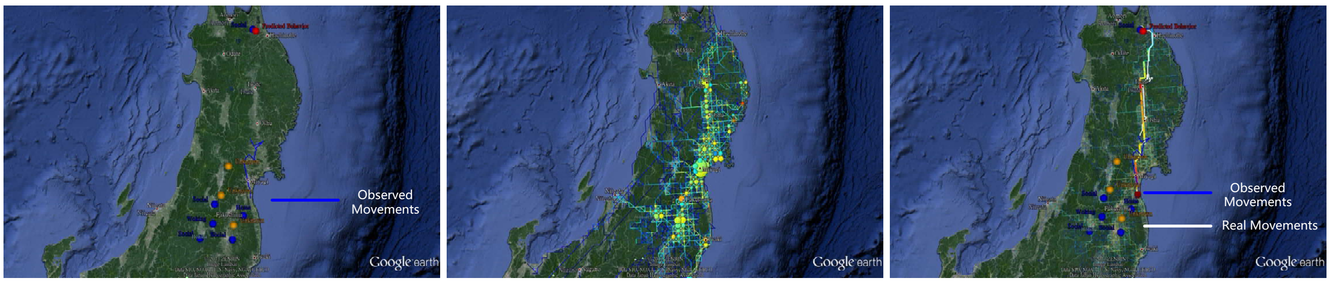
Performance evaluation: We compared the performance of our model with the performance of the baselines, and Figure 9 shows their performance. From this figure, we can see that our approach obtained a much better performance than the other competing methods on our dataset. In addition, we can see that: on the first 3 days after the earthquake, the performance of PMM for people in the Greater Tokyo Area is approximate to ours (Fig.9-a), but our method outperforms PMM much at other time. A possible explanation is that: on the first 3 days after the earthquake, many people's mobility in the Greater Tokyo Area was same to their mobility during normal times (e.g. working at daytime and go home at night). But at 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.

5.4 Evaluation of Mobility Prediction

To evaluate the accuracy of the predictive paths of people, we used three different metrics discussed in [18]. The first compares the model's most likely path estimate with the actual demonstrated path and evaluates the amount of route distance shared. The second shows what percentage of the testing paths match at least 90%



(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

Figure 8: Visualization of the results. This figure shows our prediction results of human behaviors and their possible movements. Given the persons' current observed movements (blue lines in Fig.a,d), and its important places (blue and orange circles), the possible destinations are predicted as the red circle (Fig.a,d). Meanwhile, given the learnt urban mobility graph (Fig.b,e), persons' possible movements are predicted as the bold and colorful lines (Fig.c,f), and its actual movements are shown in the white lines (Fig.c,f). The first row shows the example results of a person in the Greater Tokyo Area, and our approach predicted its possible movements at next four hours. The second row shows the person's case in Fukushima prefecture, and our model predicted its possible movements at next one day. Note that the edge color in (Fig.b,e) indicates the edge parameters of urban human mobility graph. Here, it shows the travel frequency after the earthquake, the warmer one means the higher travel frequency; and this value is normalized from 0 to 1. In addition, the color of predicted trajectories (c,f) shows the probability which is normalized from 0 to 1. The warmer one means the higher probability.

(distance) with the model's predicted path. The final metric measures the average log probability of paths in the training set under the given model. Meanwhile, we chose the approach developed by Song *et al.* [15] as the baseline model. This approach also uses the population mobility graph to predict possible population movements after large-scale disaster, but it does not take into account the important places of people and some important disaster states.

Table 1 shows the performance of our method and method of Song *et al.* [15]. From this table, we can see that our method outperforms method of Song *et al.* [15] by 7.46% to 11.08%.

6. RELATED WORK

Recently, a number of studies on human mobility patterns during disasters have been proposed [21, 22], 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 [3], likely the result of difficulties in collecting representative longitudinal data in places where infrastructure and social order have collapsed [23, 24] and where study populations are moving across vast geographical areas [3]. In contrast, auto-mobile sensor data offer a new way to circumvent methodological problems of earlier research because they offer high temporal and spatial resolution are instantaneously available, have no interview bias, and provide longitudinal data for very large populations [25, 20, 3, 23, 26, 27]. Meanwhile, human mobility or trajectory data mining [28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42] have become a very hot topic in various research fields. Zheng *et al.* [38] aim to mine interesting locations and travel sequences from GPS trajectories. Cho *et al.* [1] propose a periodic mobility model (PMM) for predicting dynamics of future human movements by using check-in data. Ye *et al.* [7] propose a HMM-based human behavior model to predict human activity from check-in data. Yuan *et al.* [42] propose a graph-based model for population mobility summarization.

More Recently, Lu *et al.* [3] 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. Song *et al.* [2] collected data from 1.6 million GPS users in Japan to mine and modeling population evacuations during the 2011 Great East Japan Earthquake and Fukushima nuclear accident, and demonstrated that the prediction of large population movements after large-scale disaster was very possible. However, due to the lack of a powerful human behavior model that is able to fully depict how different disaster factors will influence population mobility patterns, they are difficult to accurately predict behavior or mobility of individual person. Thus, in this study, we firstly try to develop a concise human behavior model for accurately predicting human mobility after large-scale disaster.

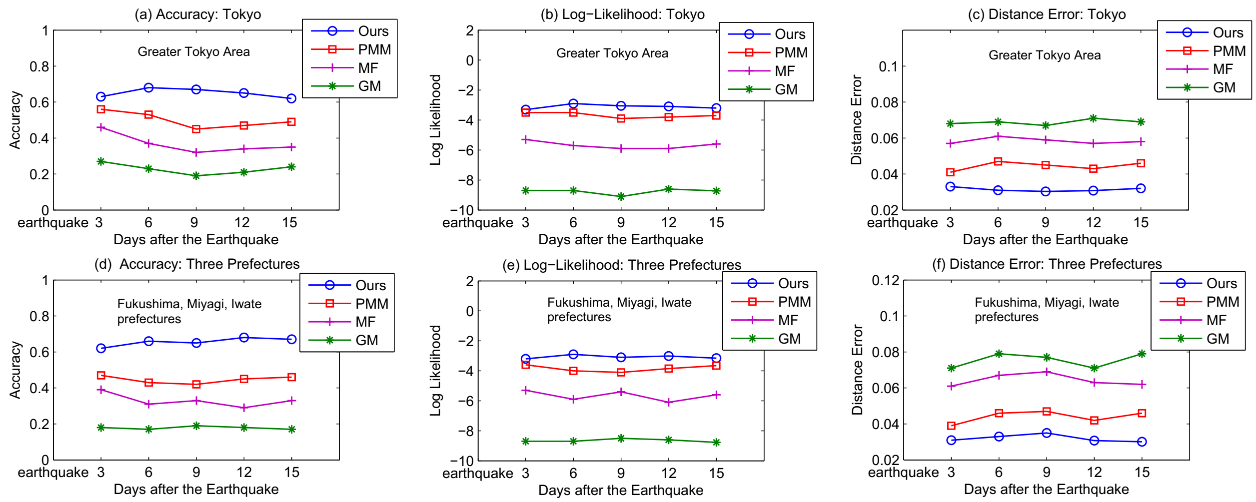


Figure 9: Evaluation of behavior prediction. This figure shows the performance evaluation of four methods with three different evaluation metrics. The first row shows the evaluation of people in the Greater Tokyo Area, and the second row shows the case of people in Fukushima, Miyagi, Iwate prefectures.

Table 1: Evaluation of Mobility Prediction

Algorithm	Matching	90% Matching	Log-Prob
Our Method (the Greater Tokyo Area)	80.68%	58.73%	-6.53
Method [15] (the Greater Tokyo Area)	72.76%	51.27%	-7.15
Our Method (Other three prefectures)	83.39%	63.36%	-5.97
Method [15] (Other three prefectures)	73.28%	52.28%	-7.33

7. CONCLUSION

In this paper, we build up a large human mobility database and several different datasets to capture and analyze human behavior and their mobility after the Great East Japan Earthquake and Fukushima nuclear accident. In addition, we develop a model of human behavior that takes into account different disaster factors for accurately predicting their behavior and mobility. The experimental results and validations demonstrate the efficiency of our behavior model, and it obtains a much better performance than previous approaches.

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 GPS service can not be incorporated into this study). Additionally, data are slightly biased towards 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 the composite disaster. A second limitation of our study is related to the difficulty in extrapolating movement patterns predicted by our predictive model for use in places outside of Japan or non-affected places by this disaster.

For future work, this research can be extended and improved in the followings: at present, the learnt behavior model is only able to applied to a specific person (learnt with its movements after disaster). In the future, we try to extend our behavior model into a general one by using transfer learning technology.

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