Intelligent System for Urban Emergency Management During 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, urban emergency management has become the especially important issue for the whole governments around the world. In this paper, we present a novel intelligent system for urban emergency management during the large-scale disasters. The proposed system stores and manages the global positioning system (GPS) records from mobile devices used by approximately 1.6 million people throughout Japan over one year. By mining and analyzing population movements after the Great East Japan Earthquake, our system can automatically learn a probabilistic model to better understand and simulate human mobility during the emergency situations. Based on the learning model, population mobility in various urban areas impacted by the earthquake throughout Japan can be automatically simulated or predicted. On the basis of such kind of system, it is easy for us to find some new features or population mobility patterns after the recent and unprecedented composite disasters, which are likely to provide valuable experience and play a vital role for future disaster management worldwide.

Introduction

The 9.0 magnitude Great East Japan Earthquake (O. Norio and Tatano 2011) occurred on 11 March 2011 off the east coast of Honshu, Japan's largest island. Since modern record keeping began in 1900, this is considered the most powerful earthquake to have occurred in Japan and is one of the five most powerful historical earthquakes worldwide (O. Norio and Tatano 2011). The Great East Japan Earthquake disrupted the public transportation systems in the Greater Tokyo Area (almost the whole metro or railway services were at a standstill), the largest metropolitan area in the world with more than 1/3 GDP of Japan, and caused large traffic chaos and urban disorders. On the other hand, many earthquake experts in Japan predicted that there would be another big earthquake at Tokyo with high probability in next five years. Facing these possible and unexpected disasters, Japan government must prepare contingency plans for them. Thus, there is an urgent need to develop an intelligent system that can understand and model the patterns of population movements o during disasters, and use this knowledge to develop simulation or predictive models for future disaster mitigation and urban emergency management.

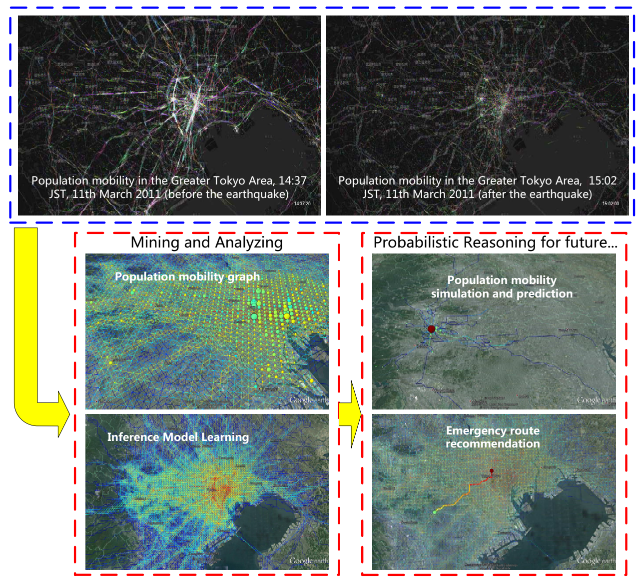

Figure 1: What kinds of experiences or model can we learn from the unprecedented composite disaster of Japan in 2011? The Great East Japan Earthquake disrupted the public transportation systems in the Greater Tokyo Area, and caused large traffic chaos and urban disorders. By mining and analyzing population mobility after the earthquake, can we learn some experiences, simulation or predictive models for future disaster relief and emergency management worldwide?

Therefore, in this paper, we present a novel intelligent system that stores and manages daily GPS records from approximately 1.6 million individuals throughout Japan over one year for urban emergency management during large-scale disaster. By mining this enormous set of Auto-GPS mobile sensor data, the proposed system can automatically analyze and understand population movements in the Greater Tokyo Area after the Great East Japan Earthquake. Based on

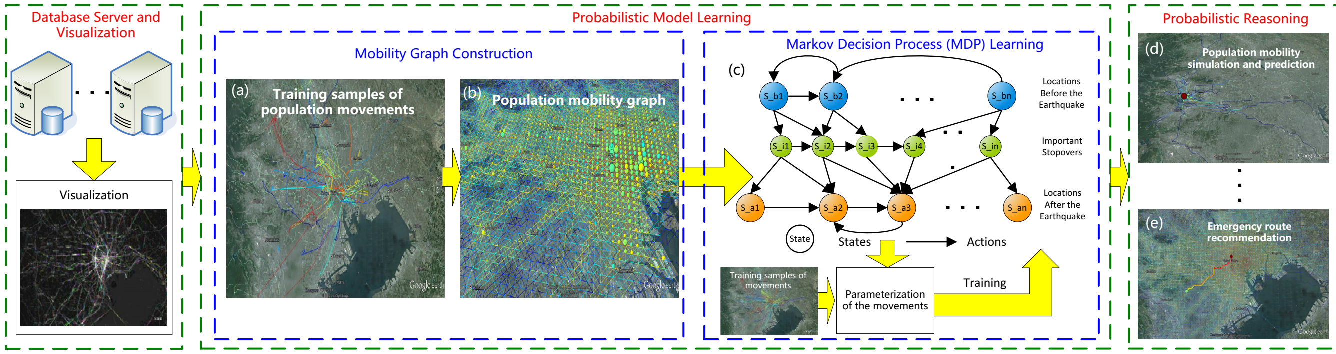

Figure 2: System overview: This figure illustrates the overall system, please see the texts for details.

these analyzed population behaviors, our system constructs a probabilistic inference model to effectively represent people's mobility patterns during this disaster. Furthermore, on the basis of the constructed model, our system can simulate or predict population mobility under various city emergency states for future disaster relief and emergency management.

The remainder of this paper is structured as follows: In the following section, the overall system is briefly introduced. Section 3 and 4 provide the details about mobility graph construction and model learning. Experimental results are presented in Section 5. Related work is briefly reviewed in Section 6, and the paper is finally summarized in Section 7.

System Overview

The overall system is illustrated in Fig.2, and it mainly contains three modules: database server and visualization module, learning module (mobility graph construction and MDP learning), and probabilistic reasoning module. The database server and visualization module stores and manages the GPS data for all the people being tracked; it provides indexing, retrieval, editing and visualization services. The mobility graph construction module is able to construct population mobility graph after the earthquake, and automatically analyze population mobility patterns and their behaviors. The MDP learning module uses these analyzed emergency behaviors to build a probabilistic model, and the probabilistic reasoning module is able to simulate or predict population mobility in various urban areas for some future emergency situations.

Mobility Graph Construction

To understand, simulate and predict human mobility during the disasters, we need a concise model to effectively represent population movements after the earthquake. Firstly, we need to construct the population mobility graph to model the relationship between various affected urban regions. It is easy to think of using transportation networks to construct it. However, most public transportation systems were not available after the earthquake occurred. Hence, in our system, we utilize the collected population trajectories after the Great East Japan earthquake to construct it through *collaborative learning* (L. Wei and Peng 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. the public transportation systems are completely unavailable again).

Region Construction: To construct the population mobility graph, we firstly need to discover connected urban areas after earthquake with the population movements (as shown in Figure 3-B). 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 (L. Wei and Peng 2012).

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, an edges is constructed between the two regions (as shown in Figure 3-C), and its edge information is estimated by the same methods as previous discussions.

In summary, the whole process of the mobility graph construction is able to be illustrated in Figure 3.

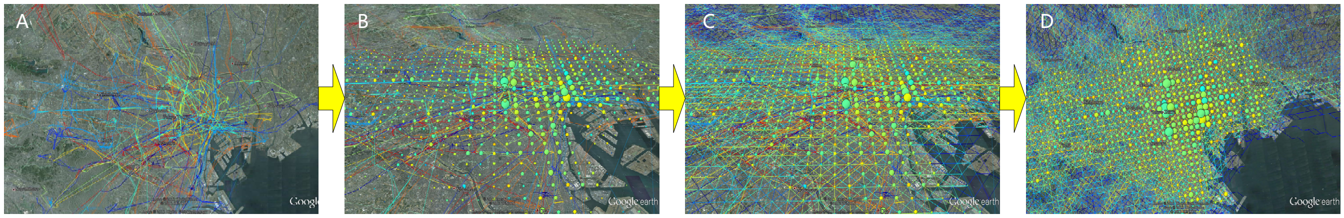

Figure 3: Mobility graph construction. Given the population trajectories after the earthquake (Fig.A), we constructed some important regions as the nodes for the graph (Fig.B). Then, we utilized these trajectories traversing the regions to derive edge connections (Fig.C). The final mobility graph was illustrated in Fig.D.

Model Learning and Probabilistic Reasoning

Inference Model Learning

Based on the constructed population mobility graph, the inference model is able to be developed by using the Markov Decision Process (MDPs) (Puterman 1994). 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 an 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:

$$cost(\zeta|\boldsymbol{\phi}) = \sum_{a\in\zeta} \boldsymbol{\phi}^\top \mathbf{f}_a = \boldsymbol{\phi}^\top \mathbf{f}_\zeta \tag{1}$$

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 (as shown in Fig.4). 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 ($frq = 0.37$, $time = 0.58$) ($A \to B$) and route 2 ($frq = 0.29$, $time = 0.62$)($B \to C$), 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 these emergency 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 (B. D. Ziebart and Dey 2008b; 2008a) to train the overall inference model.

Based on the *Maximum Entropy Principle*, the path distribution is able to be defined as:

$$P(\zeta|\boldsymbol{\phi}) = \frac{e^{-cost(\zeta|\boldsymbol{\phi})}}{\sum_{path\zeta'} e^{-cost(\zeta'|\boldsymbol{\phi})}}. \tag{2}$$

Hence, the cost weight vector $\boldsymbol{\phi}$ from demonstrated behavior is learned by maximizing the entropy of the distribution over paths subject to the feature constraints from the emergency trajectories, and it implies that we maximize the likelihood of the observed data under the maximum entropy distribution as:

$$\boldsymbol{\phi}^* = \arg\max_{\boldsymbol{\phi}} L(\boldsymbol{\phi}) = \sum_D \log P(\zeta_i|\boldsymbol{\phi}) \tag{3}$$

This function is convex for deterministic MDPs (B. D. Ziebart and Dey 2008a) and the optima can be obtained using gradient-based optimization methods. The gradient is the difference between expected empirical feature counts and the learner's expected feature counts, which can be expressed by:

$$\triangledown L(\boldsymbol{\phi}) = \widetilde{\mathbf{f}} - \sum_\zeta P(\zeta_i|\boldsymbol{\phi})\mathbf{f}_{\zeta_i} = \widetilde{\mathbf{f}} - \sum_a G_a \mathbf{f}_a, \tag{4}$$

where G_a is the expected action visitation frequencies, and is able to be computed by enumerating all paths and probabilistically count the number of paths and times in each path the particular state is visited as Algorithm 1 and Eq.(5).

Algorithm 1 employs a more tractable approach by finding the probabilistic weight of all paths from the origin s_o to a specific action a, $Z'_a = \sum_{\zeta_{o\to a}} e^{-cost(\zeta)}$, all paths from the action a to the goal g, $Z_a = \sum_{\zeta_{a\to g}} e^{-cost(\zeta)}$, and all paths from the origin to the goal, $Z_o = Z'_g = \sum_{\zeta_{o\to g}} e^{-cost(\zeta)}$. Hence, the expected action visitation frequencies G_a is computed by:

$$G_a = \frac{Z_a Z'_a e^{-cost(a)}}{Z_o}. \tag{5}$$

In summary, the inference model is able to be trained by finding the cost weight parameters with Eq.(3), Eq.(4), Algorithm 1 and Eq.(5) through the emergency trajectories dataset D. With this training model, the people's movement or behaviors during some future emergency situations is able to be easily simulated or predicted.

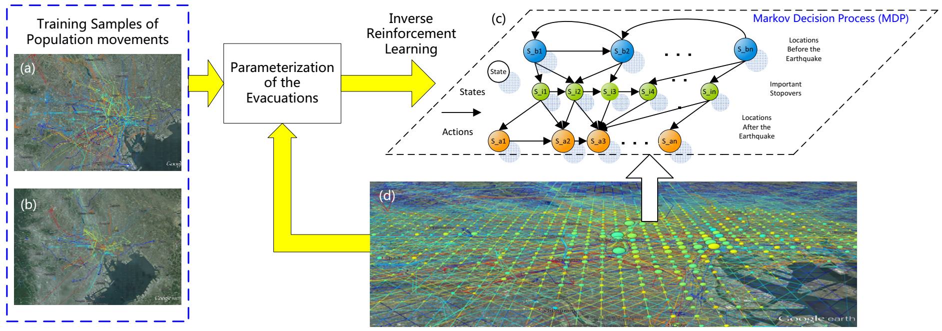

Figure 4: Inference model learning. Based on the constructed mobility graph, the inference model was able to be developed by using the Markov Decision Process (MDPs). The mobility graph provided us a deterministic MDP, the urban region (nodes) was able to be seem as *state*, the edge was the *action*, and the *path* was the parameterized trajectories by their path feature. We utilized the *Inverse Reinforcement Learning* to train the overall inference model.

Algorithm 1: Expected Action Frequency Calculation

Input: Cost weight ϕ, initial state s_o, and goal state s_g.
Output: Expected action visitation frequencies $G_{a_{i,j}}$.

Backward Pass

1. Set $Z_{s_i} = 1$ for valid goal states, 0 otherwise;
2. Recursively compute for T iterations
   $Z_{a_{i,j}} = e^{-cost(a_{i,j}|\phi)} Z_{s:a_{i,j}}$
   $Z_{s_i} = \sum_{a_{i,j} \text{ of } s_i} Z_{a_{i,j}} + 1$

Forward Pass

3. Set $Z'_{s_i} = 1$ for valid goal states, 0 otherwise;
4. Recursively compute for T iterations
   $Z'_{a_{i,j}} = e^{-cost(a_{i,j}|\phi)} Z'_{s_i}$
   $Z'_{s_i} = \sum_{a_{i,j} \text{ to } s_i} Z'_{a_{j,i}} + 1$

Summing frequencies

5. $G_{a_{i,j}} = \frac{Z'_{s_i} e^{-cost(a_{i,j}|\phi)} Z_{s_i}}{Z_{s_{\text{initial}}}}$

Probabilistic Reasoning

Based on the trained inference model, people's behaviors or movements is able to be simulated or predicted for some similar emergency situations in the future. We utilize the Bayes's rule to perform this probabilistic inference: given the partial observed movements (such as some trajectories during first several hours after the event), $\zeta_{A\to B}$, the posterior probability of the destinations is able to computed by:

$$P(\text{dest}|\zeta_{A\to B}, \phi) \propto P(\zeta_{A\to B}|\text{dest}, \phi)P(\text{dest}), \quad (6)$$

where $P(\text{dest})$ is the mobility prior in a region A, and it depends on the popular route inference (L. Wei and Peng 2012) in the mobility graph, and $P(\zeta_{A\to B}|\text{dest}, \phi)$ is likelihood, which is depended on:

$$P(\zeta_{A\to B}|\text{dest}, \phi) \propto \frac{\sum_{\zeta_{B\to dest}} e^{-cost(\zeta|\phi)}}{\sum_{\zeta_{A\to dest}} e^{-cost(\zeta|\phi)}}, \quad (7)$$

and Eq.(7) is able to be easily inferred by taking the sums over paths from A to B to each possible destination using the forward pass of Algorithm 1.

Hence, the possible population destination or routes can be simulated or predicted by the *Maximum a Posteriori* (MAP) estimation of Eq.(6).

Experimental Results

The proposed system stores and manages GPS records of approximately 1.6 million anonymized users throughout Japan from 1 August 2010 to 31 July 2011, which contains approximately 9.2 billion GPS records, more than 600GB csv files. To analyze population mobility after the earthquake in Greater Tokyo Area, we picked up approximately 95,000 persons' trajectories during 14:46 JST, 11th March 2011 to 9:00 JST, 12th March 2011 (human movements during 18 hours after the earthquake) to perform the training and testing. We set cell length as 1km, and manually labeled the region type in mobility graph. In this section, we will present the experimental results of our system, and conduct several evaluations.

Probabilistic Reasoning Results

Fig.5-A shows the training model for population mobility inference. Based on this model, given any specific urban area and some partially observed people's trajectories, our system was able to automatically simulate or predict population mobility. To show the probabilistic reasoning results during the emergency situations, we assumed that the same event occurred again, and let the training model simulate population mobility. The results in some important urban areas are shown in Fig.5-(B-D).

Meanwhile, based on the training inference model, we try to recommend some safe and fast emergency routes during emergency situations (e.g. the public transportation systems are completely unavailable again). Here, our system selected the high frequency and fastest (less travel time) ones in the mobility graph between origin and destination, and recommend them as emergency routes. Some selected results are shown in Fig.6.

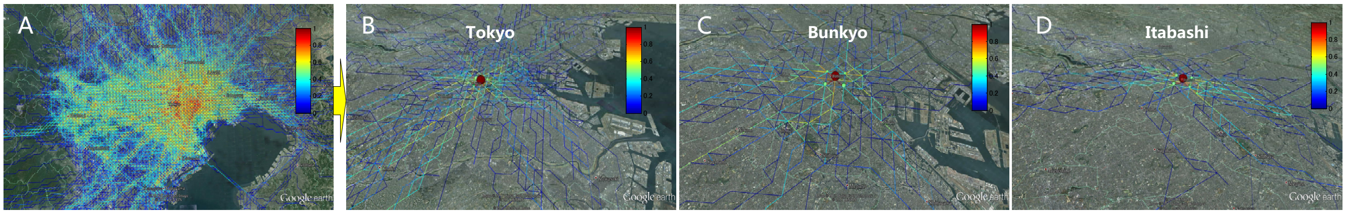

Figure 5: Learned model and simulation results. Fig.(A) shows the learned inference model. The edge color indicates the edge parameters. Here, it shows the travel frequency after the earthquake; this value is normalized from 0 to 1. Fig.(C-D) show the simulation results. Given a specific area (red circle), the possible destinations are able to be simulated by the green circles. The size of the green circle indicates the probability that large population will go there; larger circles indicate higher probabilities. Meanwhile, the trajectories show the possible movements of people, and the color shows the probability which is normalized from 0 to 1.

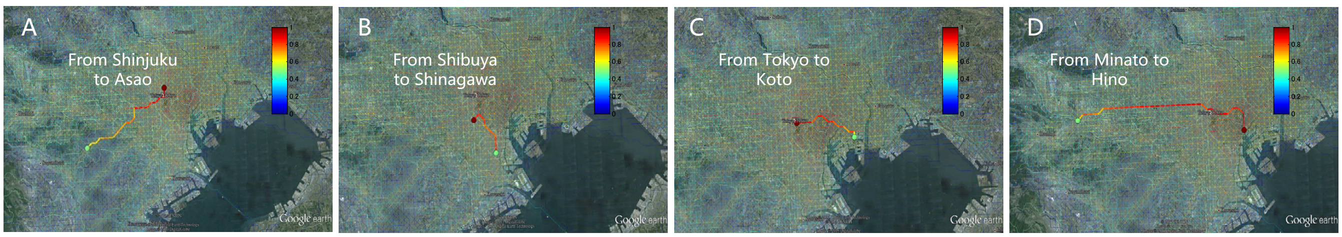

Figure 6: Recommended emergency routes. This figure shows some examples of the recommended emergency routes between different origins and destinations. The color denotes the route priority, and the warmer one means it will be better.

Performance Evaluation

We evaluated our system from two aspects: performance of mobility simulation for population flow and performance of destination prediction for individual person.

Evaluation of Population Flow Simulation To evaluate the simulation results of population flow, we performed K-fold cross-validation. The whole disaster data were randomly partitioned into three sub-samples: one sample was used as validation data while the other two were used as training data. The cross-validation process was then repeated three times, with each sub-one used exactly once as validation data. For each repetition, we computed the Jaccard similarity coefficient (P. Tan and Kumar 2005) between simulation results obtained by the training model and real population mobility distribution in testing samples for some important urban areas (some high weight nodes) in Greater Tokyo Area. The overall simulation accuracy is shown in Table 1. From this evaluation, we can see that: for most urban areas, the simulation accuracy of our system reached 86% or higher.

Evaluation of Person's Destination Prediction To evaluate the performance of destination prediction for individual person. We randomly selected 80% trajectories of the disaster data (18 hours after the earthquake) to train the inference model, and used the remaining 20% data for testing and evaluation.

Evaluation metrics: To evaluate the performance of different predictive model, we followed the work (E. Cho and Leskovec 2011), and used the following evaluation metrics.

Table 1: Simulation Accuracy

Areas	Simulation Accuracy
Tokyo	91.68%
Shinjuku	87.56%
Shibuya	89.39%
Ueno	86.25%
Ginza	88.17%
Odaiba	86.37%
Roppongi	90.38%
Urayasu	87.35%
Ikebukuro	86.28%
Nagatacho	89.09%

(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 0.6 means that 60% 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 (E. Cho and Leskovec 2011).

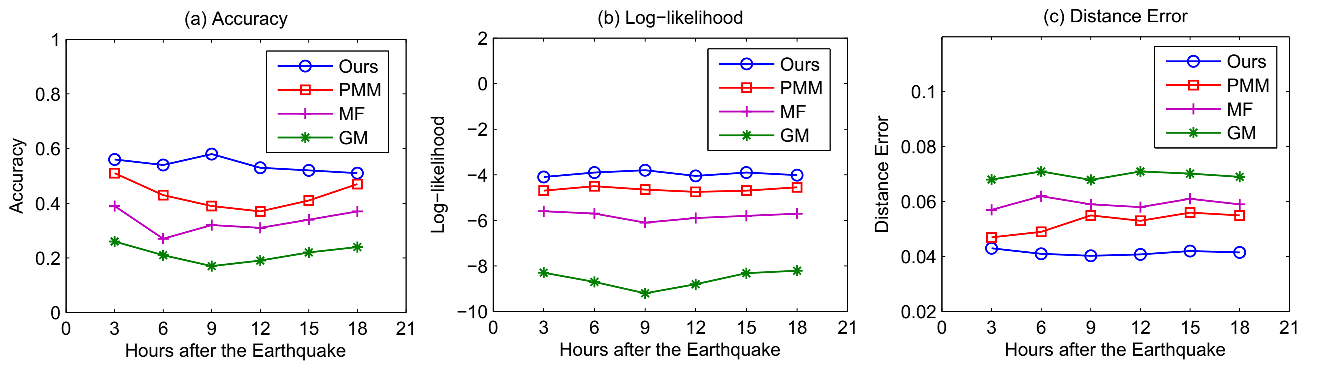

Figure 7: Evaluation of destination prediction. This figure shows the performance evaluation of four methods with three different evaluation metrics.

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.* (X. Lu and Holme 2012) also used this model to predict population mobility after the 2010 Haitian earthquake. (2) *Gaussian Model (GM):* This model has been proposed by Gonzales *et al.* (MC. Gonzalez and Barabasi 2008), and it models human movements as a stochastic process centered around a single point. This model is static in time and captures the scale of a person's movements more than anything else. (3) *Periodic Mobility Model (PMM):* This model is built on the intuition that the majority of human movement is based on periodic movement between a small set of locations. As the state-of-the-art methods, it has been proposed by Cho *et al.* (E. Cho and Leskovec 2011), which is able to predict the locations and dynamics of future human movements.

Performance evaluation: We compared the performance of our model with the performance of the baselines, and Figure 7 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. 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.

Related Work

Recently, a number of studies on human mobility patterns during disasters have been proposed (M. Moussaid and Helbing 2009; Hahm and Lee 2009), mainly focusing on small-scale and short-term emergencies (e.g. crowd panics and fires). However, research on the dynamics of population movements on a national scale during large-scale disasters (e.g.earthquakes, tsunamis, and hurricanes) is very limited (X. Lu and Holme 2012), likely the result of difficulties in collecting representative longitudinal data in places where infrastructure and social order have collapsed (JP. Bagrow and Barabasi 2011; L. Bengtsson 2011) and where study populations are moving across vast geographical areas (X. Lu and Holme 2012). In contrast, automobile 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 (X. Lu and Holme 2012; JP. Bagrow and Barabasi 2011; CM. Song and Barabasi 2010; MC. Gonzalez and Barabasi 2008; C. Song and Barabasi 2010; N. Eagle and Lazer 2009; X. Song and Shibasaki 2013a; 2013b). Meanwhile, human mobility or trajectory data mining (Z. Chen and Xie 2010; F. Giannotti and Trasarti 2011; Z. Li 2010; J. Yuan 2010; J. Yuan and Xie 2012; Z. Li and Nye 2010; J. Ye and Cheng 2013) have become a very hot topic in many research fields.

Conclusion and Discussion

In this paper, we have present an intelligent system for population mobility analysis and reasoning during large-scale disaster, and the experimental results and evaluations demonstrated that the accurate simulation or prediction of large population mobility in severe disasters or emergency situations were seem to be possible.

For future work, our system can be extended and improved in the followings: Obviously, people's mobility patterns in emergency situations are very complicated, and will be influenced by various factors. Fortunately, the inference model of the system is a general model, and is very easy to be extended. Hence, we need to study and consider more factors that will influence human mobility in emergency situations, and develop the more accurate inference model for it. On the other hand, the recommendation module of our system for emergency routes is still very simple. Currently, we just recommend some high frequency visited or fast routes for persons. In the future, some deep models and more factors for emergency routes recommendation should be carefully explored.

Acknowledgements

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