Available online at www.sciencedirect.com

ScienceDirect

Procedia Economics and Finance 18 (2014) 33 – 38

Procedia Economics and Finance

www.elsevier.com/locate/procedia

4th International Conference on Building Resilience, Building Resilience 2014, 8-10 September 2014, Salford Quays, United kingdom

Quantifying and Comparing Human Mobility Perturbation during Hurricane Sandy, Typhoon Wipha and Typhoon Haiyan

Qi Wang[a], John E. Taylor[a,*]

[a] Charles E. Via, Jr. Department of Civil and Environmental Engineering, 120 Patton Hall, Blacksburg, VA 24060, U.S.A

Abstract

Climate change has intensified tropical cyclones, resulting in several recent catastrophic hurricanes and typhoons. Such disasters impose threats on populous coastal urban areas, and therefore, understanding and predicting human movements plays a critical role in disaster evacuation, response and relief. Despite its critical roles, limited research has focused on tropical cyclones and their influence on human mobility. Here, we studied how severe tropical storms could influence human mobility patterns in coastal urban populations using individuals' movement data collected from Twitter. We selected three significant tropical storms, including Hurricane Sandy, Typhoon Wipha, and Typhoon Haiyan. We analyzed the human movement data before, during, and after each event, comparing the perturbed movement data to movement data from steady states. We also used different statistical analysis approaches to quantify the strength and duration of human mobility perturbation. The results suggest that tropical cyclones can significantly perturb human movements by changing travel frequencies and displacement probability distributions; however, the nature-derived Lévy Walk model still predominantly governs human mobility. Also, human mobility exhibits a surprisingly mild and brief perturbation for Hurricane Sandy and Typhoon Wipha, while the duration of disturbance was much longer for Typhoon Haiyan. Our finding that the Lévy Walk model can still predict human mobility suggests that bio-inspired examinations of human mobility patterns may uncover solutions to improve disaster evacuation, response and relief plans.

Selection and/or peer-reviewed under responsibility of the Centre for Disaster Resilience, School of the Built Environment, University of Salford.

Keywords: Geosocial Networking; Human mobility; Hurricanes; Lévy Walks; Tropical Cyclones; Typhoons

* Corresponding author. Tel.: +1-540-231-0972 ; fax: +1-540-231-7532 .
E-mail address: jet@vt.edu .

2212-5671
Selection and/or peer-reviewed under responsibility of the Centre for Disaster Resilience, School of the Built Environment, University of Salford.
doi:10.1016/S2212-5671(14)00910-1

1. Introduction

Natural disasters exert profound impact on the world population. Overall, they are becoming more and more intensified owing to global climate change (Ferris et al., 2013). Such intensification is observed in tropical cyclones. The frequency of Atlantic tropical cyclones has increased over the last 100 years, and the increasing trend has accelerated since the 1980s (Landsea et al., 2010). By 2100, the power of tropical cyclones is predicted to increase by 2-11% (Knutson et al., 2010). Intensifying tropical cyclones severely threaten coastal urban areas where human mobility dynamics are active and complex. Several tropical cyclones have caused extensive damage to cities located along coastlines in recent years. Typhoon Haiyan destroyed Tacloban, a city with a population of more than 220,000 (BBC, 2013). Hurricane Sandy caused at least 43 deaths and up to $50 billion in economic loss in New York City, making it the most expensive natural disaster in 2012 (Ferris et al., 2013). Typhoon Wipha brought record-breaking heavy rain storms to Tokyo and forced 60,000 people to have their flights canceled (Gayo-Avello, 2012). The tragic loss of life, the immense human suffering and severe economic loss from these events call for innovative research and technologies to improve disaster evacuation, response and relief.

Understanding and predicting human movements plays a critical role in disaster evacuation, response and relief. Breakthroughs in the field of information technology and geographical location have allowed for large amounts of data to be easily acquired regarding human movements. Researchers have used currency circulation, GPS, wireless services, and geo-social networking media to collect human mobility data (Brockmann et al., 2006, Gonzalez et al., 2008, Song et al., 2010a). However, limited research has attempted to understand the perturbation in human mobility during natural disasters. Therefore, in this paper, we examine how mobility in three different coastal cities is influenced by tropical cyclones. Individuals' movement data is analyzed to identify any disturbance in human mobility during tropical cyclones.

2. Background

A considerable amount of existing research has examined and improved our understanding of general human mobility patterns. Three common patterns have been found. First, using both currency circulation data and mobile phone data, research found human movements follow power-law distribution with β values ranging from 1.59 to 1.88 (Brockmann et al., 2006, Gonzalez et al., 2008, Hawelka et al., 2013, Cheng et al., 2011). The finding means human movements can generally be described by the Lévy Walk model which is typically found in animals' movement patterns (Ramos-Fernandez et al., 2004). Second, research has shown that individual movement trajectories exhibited similar shapes after being rescaled by the radius of gyration (Gonzalez et al., 2008). Third, movement trajectories demonstrate uneven visitation frequency of different locations, repeatedly returning to certain locations while being less likely to visit new ones. Song et al. (2010a) investigated a large dataset which contained 1 million mobile phone users for a year-long period. They observed three unique characteristics of human mobility which both the Lévy Walk model (Brockmann et al. 2006) and the continuous-time random-walk model (Kimura and Saito, 2006, Wang and Taylor, 2014b) failed to explain. These characteristics were: (1) a decreasing tendency of a person to visit new locations; (2) an uneven visitation frequency to different locations; and (3) an ultraslow diffusion, which meant people tended to return to the same locations (e.g., home, office, etc.). Based on these observations, Song et al. (2010b) developed a new individual-mobility model by adding two unique generic mechanisms: exploration and preferential return. While this new model was more representative of human mobility patterns compared to other models, its strength was in capturing long-term spatial and temporal scaling patterns.

Researchers have also studied human movement at the city scale. At this level, periodic modulations characterize human mobility (Song et al., 2010a). Noulas et al. (2012) studied human mobility in 31 large cities around the world, and found that the global movements followed a power-law distribution. They also found human mobility in all the cities studied followed almost the same pattern. Some studies also found people exhibit characteristics of periodicity to return to primary locations (Cho et al., 2011, Liang et al., 2012) because they are governed by the 24 hour and 7 day temporal circles. Furthermore, human movements have been shown to follow highly efficient trajectory configurations during their daily movements. Schneider et al. (2013) found people perform their daily trips with high efficiency by following only 17 configurations of trajectories out of over a million possible trajectories.

While human mobility studies have improved our knowledge about general mobility patterns, it is intuitive to assume that the change of environment may perturb these patterns. On one hand, extreme events and disasters can perturb human routine movements. Bagrow et al. (2011) used mobile phone billing data to track people's communication in 8 emergency events (bombing, earthquake, etc.) and 8 non-emergency events (sports, concerts, etc.). The results showed that the emergency information tends to diffuse globally while the non-emergency information is more spatially constrained. Horanont et al. (2013) studied the relation between weather conditions and people's everyday activities. They found that some types of weather conditions can significantly influence human movements, although such influence shows high diversity on individuals. These findings showed that unusual events and the change of natural environment could influence people's activities. On the other hand, natural disasters can cause population migration. Morrow-Jone and Morrow-Jone (1991) studied an 8-year dataset of movers and identified that natural disasters could cause involuntary migration. Bengtsson et al. (2011) tracked population movements in Haiti using cell phone data, and found that earthquake and disease infection caused as much as 20% of population to leave the capital city, Port-au-Prince.

While studies show that human movement trajectories during disasters would deviate from steady states, limited research has quantified the changes of human mobility patterns when urban areas are visited by tropical cyclones. We do not yet know quantitatively whether the bio-inspired Lévy Walk still governs human mobility during tropical cyclones and, if not, what the changes are. The lack of research may be attributed to the inherent unpredictability of disasters and resulting data scarcity. The fact that Hurricane Sandy had caused "extensive damage" before landing the U.S. illustrates the difficulties in predicting these disaster events even in a developed country, and thus, highlights the challenge of protecting urban dwellers. A better understanding of human mobility under the influence of tropical cyclones derived from a comparative analysis from different disaster events is necessary.

3. Methodology

To quantify the perturbation and resilience of human mobility under the influence of tropical cyclones, we adopted the following methodology. First, several hypotheses were developed regarding the influence of tropical cyclones. Second, we introduce the method of collecting empirical human mobility data. Then the data were used to analyze three storm events affecting three different urban areas.

3.1 Data Collection

Much empirically grounded human mobility research utilizes mobile phones to track human mobility (Gonzalez et al., 2008, Schneider et al., 2013, Song et al., 2010a, Song et al., 2010b, Wesolowski et al., 2012). The data precision of these studies is limited to the coverage area of each mobile phone tower, which is typically around $3km^2$. While such precision has been instrumental in developing an understanding of general patterns of human mobility over larger scales (e.g., a state or a country), it may lack the necessary precision to capture mobility changes caused by disasters and other extreme events that unfold at smaller scales (e.g., a city).

To overcome the limitation, Twitter was used to collect high-resolution human mobility data in this study. Twitter is an online social networking media that allows people to post text messages that are limited to 140 characters, called tweets. It has over 640 million active users who post about 500 million tweets per day (Brain, 2014). Users can also select to let Twitter add location information, called a geotag, to each tweet they post. Each geotag contains the exact coordinate at which the tweet was posted. Researchers have recently adopted the Twitter platform to study communication and geo-social networking (Wang and Taylor, 2014a, Wang and Taylor, 2014b). Using the Twitter public API, we developed a 2-step information collection method described in the following sections.

Step 1: Collect Tweets with Geotags

We first collected all tweets that contain geotags. A geotagged tweets streaming module was developed. This module establishes a continuous connection between a computer in our research lab and the Twitter server. The connection streams every tweet that contains a geotag. Tweepy, a Python package for implementing the Twitter API, was used to develop the module. In addition to the exact geographical coordinate, each streamed tweet contains a list of extra information, including the tweet's ID, place name, the name and ID of the user who posted the tweet, and the time stamp of when it was posted. The collected tweets were stored in a database called **GeoTweets**. The data collection started on October 29, 2012, and lasted for over a year. We collected approximately 3.9 million geotagged tweets each day.

Step 2: Filter Tweets in a Specific Urban Area

In this step, we filter the tweets stored in the GeoTweets database based on the information of tropical cyclones and their affected urban areas. After a tropical cyclone occurred, we would identify if it had impacted certain urban areas. If it did, the geographical boundary was determined. Then we retrieved all the data collected during the days when, and several days before and after, the tropical cyclone stuck the area. To do this, we tested if the geographical coordinate of each tweet was within the geographical boundary of the urban area. As mentioned before, the geospatial information was embedded in each tweet. Therefore, we designed a location filter module for this step. The module checks each tweet in the **GeoTweet** database and retrieves its geographical coordinate. If the coordinate was located in the city, the tweet was selected and imported into a second database, **[CityName]Tweets**.

The effort allowed us to obtain human mobility data of the three previously mentioned significant tropical storms that struck three coastal urban areas. These included; (1) Hurricane Sandy in New York City, (2) Typhoon Wipha in Tokyo, and (3) Typhoon Haiyan in Tacloban and its adjacent areas. The data summary is presented in Table 1.

Table 1. Data Summary

	Hurricane Sandy	**Typhoon Wipha**	**Typhoon Haiyan**
Data Collection Start Time	5pm Oct. 29, 2012	3am Oct. 6, 2013	11pm Nov. 4, 2013
Data Collection Finish Time	8pm Nov. 10, 2012	3am Oct. 25, 2013	11pm Nov. 28, 2013
Number of Days	12	19	24
Average # Data Points Collected per Day	56,802.83	38,643.68	4,673.00
Standard Deviation of Data Points	4,850.49	3,459.84	1,379.35
Number of Twitter Users in Dataset	53,934	60,236	9,614
Tropical Cyclone Landfall	8pm Oct. 29, 2012	Early Oct. 15, 2013*	5am Nov. 8, 2013

*Typhoon Wipha did not make landfall. It skirted Japan's eastern coastline.

3.2 Data Analysis

We conducted multiple analyses on the empirical human mobility data collected from Twitter. First, we calculated all the distances between consecutive locations from each distinct user, called displacements. The distance between two coordinates was calculated using the Haversin formula (Robusto, 1957):

$$\Delta r = 2r \times \sin^{-1}\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos\phi_1\phi_2 \sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right)}\right)$$

Where r is the earth radius, which approximately equals to 6,367,000 meters, ϕ is the latitude, and φ is the longitude. After finding all the displacements, the numbers of trips in different range of distances for each 24-hour period (Hurricane Sandy and Typhoon Wipha) or 72-hour period (Typhoon Haiyan) were calculated. We set 72-hours as a single time unit for Typhoon Haiyan due to the smaller population density and longer typhoon duration in Tacloban, Philippines.

Then we fitted the displacement data to truncated power-law distribution as suggested in previous research to ascertain whether the Lévy Walk model still can predict human mobility (Klaus et al., 2011, Clauset et al., 2009, Gonzalez et al., 2008). Truncated power-law distribution can be captured by the following equation:

$$P(\Delta r) \propto \Delta r^{-\beta} e^{-\lambda \Delta r}$$

Where Δr is the displacement, β is the scaling parameter, and λ is the exponential cutoff value. To test the goodness of fit, we conducted a Maximum Likelihood Estimation test to compare truncated power-law distribution to both exponential distribution and lognormal distribution. The Python package *powerlaw* was used to fit the data to power-law distribution and conduct Maximum Likelihood Estimation.

4. Results and Discussion

By analyzing the displacement data, we found the number of trips within different ranges of distances during the three tropical cyclones (illustrated in Figure 1). Figure 1a shows that during Hurricane Sandy, people in New York City increased their frequency of trips that were less than 1km by 21.7%, but substantially reduced the trips over 5km by 65.0%. During Typhoon Wipha, we observed minimal changes on the numbers of trips with distances ranging from 100 m to 10 km, only 4.45%. Individuals increased their frequency of trips less than 100 m by 44.3%, and decreased the frequency of trips over 10 km by 20.4% (Figure 1b). For Typhoon Haiyan, we compared human mobility for the 3-day period before the landfall of Haiyan and the 3-day period during and immediately after the landfall of Haiyan. The number of trips dropped by 85.9% overall, and travels over 5 km were nearly non-existent after the landfall (Figure 1c). The results demonstrate that tropical cyclones cause perturbation in human movements.

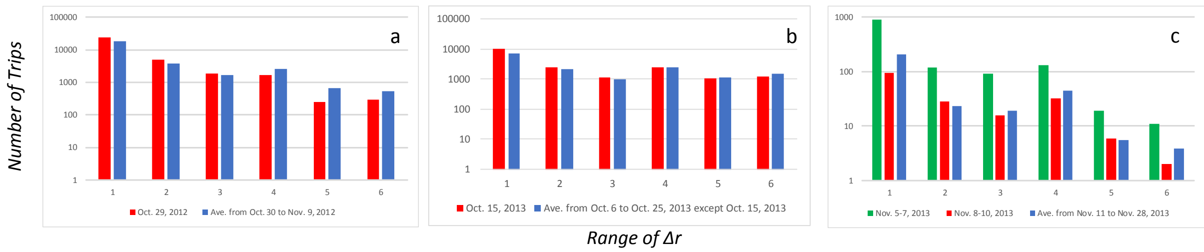

Figure 1. Numbers of Trips in Different Range of Distances for Each Time Period

We fitted the displacement data from each time period to the Lévy Walk model and conducted the Maximum Likelihood Estimation test. The results from data fitting show that in most cases power-law still describes human mobility though there are some exceptions. For Hurricane Sandy and Typhoon Wipha, each daily displacement data fit with power-law distribution better than both lognormal distribution and exponential distribution (p-value<0.001). For Haiyan, while the truncated power-law fits better than exponential distribution for all the eight periods, its advantage over lognormal distribution is not always significant. The results show that the Lévy Walk model governs human mobility even during tropical cyclones unless the storm is unusually strong.

5. Conclusions

Human mobility in urban areas can be influenced by natural and man-made disasters, and coastal cities are especially vulnerable to tropical cyclones. Existing research has reported that the change of natural environment could cause behavioral change and temporary or even permanent human migrations. In this study we collected empirical human movement data using Twitter to discover whether human mobility is perturbed by tropical cyclones. The data were analyzed to identify and quantify human mobility perturbation from steady states. Our findings demonstrate that tropical cyclones: (1) can cause human mobility perturbation; and (2) are unlikely to deviate from the power-law that governs human mobility unless the tropical cyclones are extraordinarily powerful.

The results from the empirical data revealed that tropical cyclones change the frequency of human travels, often increasing short distance trips and suppressing long distance ones. Such finding extends previous research (Bagrow et al., 2011, Horanont et al., 2013) by specifically examining the influence from tropical cyclones. We also found that, despite the perturbation, power-law still governs human mobility in most of the time periods. This result supports the findings from studies on general human mobility patterns (Brockmann et al., 2006, Cheng et al., 2011, Gonzalez et al., 2008, Hawelka et al., 2013). While previous research did not distinguish between human mobility patterns in perturbation states or steady states, we show that the animal-derived Lévy Walk model is still applicable even during the visits of tropical cyclones. Such finding highlights the inherent resilience of human mobility. It suggests that mobility patterns in coastal cities possess impressive resilience and adaptability to tropical cyclones.

While this study is an attempt to quantify human mobility perturbation, future research can build on the results of this study by examining more tropical cyclones and examining other influential factors as independent variables that may correlate with mobility patterns (e.g., differing availability of public transportation means). Such future research efforts will help determine which factors significantly contribute to human mobility perturbation. Also, considering the fact that the Lévy Walk model still appears to govern human behavior even in perturbed states, future research can look to nature to identify bio-inspired solutions to cope with the disturbance brought by tropical cyclones and other types of natural disasters. This will help policy makers and practitioners to better predict human movements and improve disaster evacuation, response, and recovery plans.

Acknowledgements

This study is supported by the National Science Foundation under Grant No. 1142379. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References:

Bagrow, J. P., Wang, D. & Barabasi, A.-L. 2011. Collective response of human populations to large-scale emergencies. *PloS one,* 6**,** e17680.
Bbc 2013. Tacloban: City at the centre of the storm.
Bengtsson, L., Lu, X., Thorson, A., Garfield, R. & Von Schreeb, J. 2011. Improved response to disasters and outbreaks by tracking population movements with mobile phone network data: a post-earthquake geospatial study in Haiti. *PLoS medicine,* 8**,** e1001083.
Brain, S. 2014. *Twitter Statistics* [Online]. Available: http://www.statisticbrain.com/twitter-statistics/ [Accessed January 10, 2014.
Brockmann, D., Hufnagel, L. & Geisel, T. 2006. The scaling laws of human travel. *Nature,* 439**,** 462-465.
Cheng, Z., Caverlee, J., Lee, K. & Sui, D. Z. 2011. Exploring Millions of Footprints in Location Sharing Services. *ICWSM,* 2011**,** 81-88.
Cho, E., Myers, S. A. & Leskovec, J. Friendship and mobility: user movement in location-based social networks. Proceedings of the 17th ACM SIGKDD international conference on Knowledge discovery and data mining, 2011. ACM, 1082-1090.
Clauset, A., Shalizi, C. R. & Newman, M. E. 2009. Power-law distributions in empirical data. *SIAM review,* 51**,** 661-703.
Ferris, E., Petz, D. & Stark, C. 2013. The Year of Recurring Disaster: A Review of Natural Disasters in 2012. The Brokings Institution.
Gayo-Avello, D. 2012. " I Wanted to Predict Elections with Twitter and all I got was this Lousy Paper"--A Balanced Survey on Election Prediction using Twitter Data. *arXiv preprint arXiv:1204.6441*.
Gonzalez, M. C., Hidalgo, C. A. & Barabasi, A.-L. 2008. Understanding individual human mobility patterns. *Nature,* 453**,** 779-782.
Hawelka, B., Sitko, I., Beinat, E., Sobolevsky, S., Kazakopoulos, P. & Ratti, C. 2013. Geo-located Twitter as the proxy for global mobility patterns. *arXiv preprint arXiv:1311.0680*.
Horanont, T., Phithakkitnukoon, S., Leong, T. W., Sekimoto, Y. & Shibasaki, R. 2013. Weather Effects on the Patterns of People's Everyday Activities: A Study Using GPS Traces of Mobile Phone Users. *PloS one,* 8**,** e81153.
Kimura, M. & Saito, K. 2006. Tractable models for information diffusion in social networks. *Knowledge Discovery in Databases: PKDD 2006.* Springer.
Klaus, A., Yu, S. & Plenz, D. 2011. Statistical analyses support power law distributions found in neuronal avalanches. *PloS one,* 6**,** e19779.
Knutson, T. R., Mcbride, J. L., Chan, J., Emanuel, K., Holland, G., Landsea, C., Held, I., Kossin, J. P., Srivastava, A. & Sugi, M. 2010. Tropical cyclones and climate change. *Nature Geoscience,* 3**,** 157-163.
Landsea, C. W., Vecchi, G. A., Bengtsson, L. & Knutson, T. R. 2010. Impact of Duration Thresholds on Atlantic Tropical Cyclone Counts*. *Journal of Climate,* 23**,** 2508-2519.
Liang, X., Zheng, X., Lv, W., Zhu, T. & Xu, K. 2012. The scaling of human mobility by taxis is exponential. *Physica A: Statistical Mechanics and its Applications,* 391**,** 2135-2144.
Morrow-Jone, H. A. & Morrow-Jone, C. R. 1991. Mobility due to natural disaster: Theoretical considerations and preliminary analyses. *Disasters,* 15**,** 126-132.
Noulas, A., Scellato, S., Lambiotte, R., Pontil, M. & Mascolo, C. 2012. A tale of many cities: universal patterns in human urban mobility. *PloS one,* 7**,** e37027.
Ramos-Fernandez, G., Mateos, J. L., Miramontes, O., Cocho, G., Larralde, H. & Ayala-Orozco, B. 2004. Lévy walk patterns in the foraging movements of spider monkeys (Ateles geoffroyi). *Behavioral Ecology and Sociobiology,* 55**,** 223-230.
Robusto, C. 1957. The cosine-haversine formula. *The American Mathematical Monthly,* 64**,** 38-40.
Schneider, C. M., Belik, V., Couronné, T., Smoreda, Z. & González, M. C. 2013. Unravelling daily human mobility motifs. *Journal of The Royal Society Interface,* 10.
Song, C., Koren, T., Wang, P. & Barabasi, A.-L. 2010a. Modelling the scaling properties of human mobility. *Nat Phys,* 6**,** 818-823.
Song, C., Qu, Z., Blumm, N. & Barabási, A.-L. 2010b. Limits of predictability in human mobility. *Science,* 327**,** 1018-1021.
Wang, Q. & Taylor, J. E. 2014a. Energy saving practice diffusion in online networks. *Energy and Buildings,* 76**,** 622-630.
Wang, Q. & Taylor, J. E. 2014b. Quantifying Human Mobility Perturbation and Resilience in Natural Disasters. *arXiv preprint arXiv:1402.1987*.
Wesolowski, A., Eagle, N., Tatem, A. J., Smith, D. L., Noor, A. M., Snow, R. W. & Buckee, C. O. 2012. Quantifying the impact of human mobility on malaria. *Science,* 338**,** 267-270.