A Hybrid Mobility Model based on Social, Cultural and Language Diversity

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Abstract – **Human Mobility Models (HMMs) have become increasingly relevant in different application domains including networks designed for data dissemination protocols. Most existing HMMs consider the temporal and spatial features of human mobility. In addition, many recent HMMs based on social networks have begun to take into account social factors, which naturally influence the results of the HMMs. Unfortunately, these mobility models do not focus on the impact of several important social factors that can affect a person's actions, such as language, citizenship, and culture. This paper introduces a hybrid human mobility model that integrates social behavior, cultural and language factors into HMMs in order to measure their effect on human mobility, as well as temporal and spatial features. Results demonstrate the feasibility of the proposed model.**

Keywords – **Human Mobility Models; Social Networks; Cultural Impact; Opportunistic Networks; Hybrid Mobility Model.**

I. INTRODUCTION

Personal mobile communication devices, such as smart phones, PDAs, and tablets are becoming increasingly ubiquitous with every passing day. The demand and usage patterns of such devices have emerged as contact-based opportunistic and delay tolerant networks, where data is transmitted through nearby relay nodes. The network topology and data dissemination protocols of these networks are greatly influenced by the movement of the people carrying the devices which compose the nodes of the network. This constant change can have significant performance impacts on the networks, as well as additional consequences. Human Mobility Models (HMMs) present a method which can be used to model these types of dynamic networks. HMMs can be used to: model telecommunications networks, study the epidemiological patterns of infectious agents, study the sociological patterns of "social networks", and in civil engineering for city planning and architecture, transportation route planning, and many other fields. As shown from the examples above the utility of this type of modeling is widely recognized and used in many different academic fields and research projects; several modeling methods have been proposed to implement HMMs in the past [1-18].

Human mobility depends on a multitude of temporal, spatial and behavioral factors. A simple example would be a person's stay in their office and home during the day, and the extra work into the nights from Monday to Friday. Another example is an individual who likes shopping (a behavioral trait), will likely spend more time in shopping malls during weekends, other people' social, cultural and language traits can also have a great impact on HMMs. Members of a particular ethnic/religious/linguistic group will obviously prefer to go to places and events which that are part of their background. They are also much more likely to associate with other members of their group than people outside of it. These tendencies create a noticeable clustering effect in the results of many HMMs. Existing HMMs consider one or two of these factors and rarely take into account the complete cultural context of the demographic which is being examined. For instance, location-based mobility models consider only the spatial feature of human mobility, and social-based models consider behavioural patterns of the individuals involved. Thus, any statistical distributions built on social-based models cannot evaluate the spatial factors present (i.e. movement length), and vice versa. Social-based mobility models do not focus on the impact of these various factors that impact the formation of a mobile community, and many cannot reproduce properties of contact graphs in real traces.

This paper introduces a hybrid human mobility model that integrates the social, cultural and linguistic factors which impact HMMs that also include the temporal and spatial features in the model. This model was constructed using real data traces from the IEEE INFOCOM 2006 conference [6, 20], which consists of the contact data of participants, along with their social and cultural background. Using these conversations, the model placed the conference participants into two groups based cultural (i.e., language and country) and academic (i.e., affiliation and area of studies) backgrounds. Some additional factors which were used include the number of participants and links in each group. The criterion determined that cultural features have more influence on human mobility than academic features. The models were also validated with real data traces.

The remainder of this paper is organized as follows. Section II presents the basic steps to build a mobility model and define some terminologies. Section III presents several existing mobility models. Section IV presents the proposed hybrid mobility model. Section V presents the evaluation of the model by comparing it with real data traces. Finally,

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Section VI concludes the paper and presents ideas for future work.

II. PRELIMINARIES

There are several phases to building a HMM. First, data is collected using GPS, Wi-Fi access points, Bluetooth and other short range communication networks. The data collection results from real life data traces of human mobility. In the next step, data traces are analyzed using theoretical approaches and statistical analysis tools. Different data mining approaches are also used in this step. The statistical distribution of inter-contact time, contact frequencies, contact location, duration and other metrics produce recognizable mobility pattern, and allow for HMMs to be generated. After these models are constructed, they can be used to design data forwarding, routing and dissemination protocols of opportunistic ad hoc networks. Fig. 1 illustrates the block diagram of building a HMM.

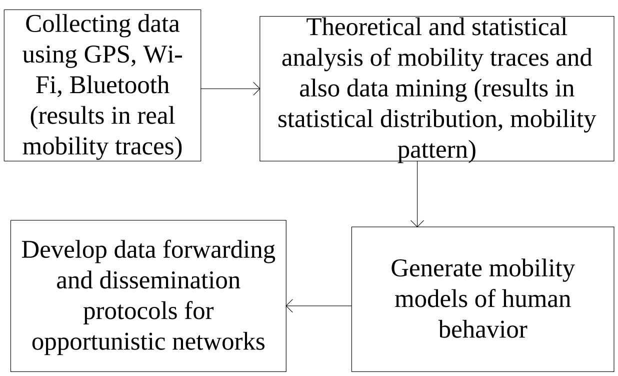

Figure 1. Block diagram of Human Mobility Models

In the HMM proposed here, contact information of the IEEE INFOCOM 2006 participants include the city and country which they came from, their country of residence, and their language, affiliation, and area of specialization. After this data was used to generate a contact graph, several metrics have been used to evaluate the results. One metric is "betweenness", which represents the number of times an edge of a contact graph is used to traverse from a node to another node in the graph. For instance, edges {B, F} {E, H} and {E, J} in Fig. 3 will have the highest betweenness since they are used to traverse between two communities or groups, identified in that contact graph. Another important metric used to analyse the graphs which was the Node degree, which is defined as the number of contacts or links from each node to all other nodes in the network.

III. RELATED WORK

Most existing mobility models fail to capture the confrontation and collaboration characteristics of mobile nodes, which are carried by people in many different environments. Work done by Cai J. and Wu W. introduces a mobility model which features the confrontation and collaboration (C&C) [1] characteristics of mobile nodes in military scenario. In this model, authors include confrontation and collaboration characteristics, such as velocity distributions, mutual synergies, creation, destruction and terrain factors and then use it to analyze the effectiveness of these characteristics in this model and compare the performance of AODV protocol in the proposed model with the traditional random waypoint model. The proposed model is implemented in two parts. In the first part, namely, Game Ordain Module (GOM) creates a virtual battlefield environment in a real-time strategy game. In the second step, mobile traces are extracted and processed using Data Process Module (DPM). Then, the mobility model is used to simulate and evaluate the performance of network routing protocols. However, this model cannot mimic the actual battlefield confrontation and collaboration characteristics since the battlefield data are generated using GOM, which might fail to capture many dynamic battlefield characteristics. Human Mobility Obstacle (HUMO) model proposed in [12] is another such obstacle-aware human mobility model for ad hoc networks. In HUMO, nodes move around the obstacle in a natural and realistic way. Every time an obstacle is encountered between the node's current and destination position, the node moves to the obstacle position that is closest to the destination point (apex position). The node continues this process until it reaches the destination. HUMO functions in scenarios such as natural disasters, battlefield and healthcare scenarios or in any other situation where obstacles are encountered between communication devices or nodes, which can be defined from sources such as firemen, police, or soldiers who are moving while carrying mobile communication equipment, which has integrated tracking abilities built into it. This model works both in node movement and signal propagation modeling. However, this mobility model does not consider social behavior of users, which is one of the most important parameters of human mobility.

The formation of ad hoc networks is greatly influenced by the social behavior of humans, due to the existence of a relationship between human social interactions and social attributes. However, most existing mobility models do not take social networks (i.e., user's social interactions) into consideration. The Wang J. et al. study [15] examines the relationship of the movement of users with their social attributes and introduces a Social Attribute-based Mobility Model (SaMob). In this model, an attractor matrix representing the relationship of human relative movements is used to model a user's mobility in Ad hoc networks.

In SaMob, an assortative coefficient, r, is calculated in order to quantify the level of assortative mixing. If there is no assortative mixing, then $r = 0$. For dissortative mixing, r will be negative. After this calculation, an attribute matrix is calculated in order to represent the value of each attribute which is associated with a user. An attribute matching matrix is then calculated, which assigns 1 if the attribute value of two different users matches; otherwise it will be equal to 0. Finally, an attractor matrix is calculated as the mean of *m* attribute values associated between two users. In SaMob, an HMM is established by initializing a user's community. There exists several community found methods in social networks. Most of these methods depend on social network connections, which are expressed by the attractor matrix described above.

Simulation results show that SaMob can model a user's mobility accurately and efficiently. Fig. 2 illustrates the network formation of SaMob with three communities, where members in each community are tightly connected and members between two communities are loosely connected.

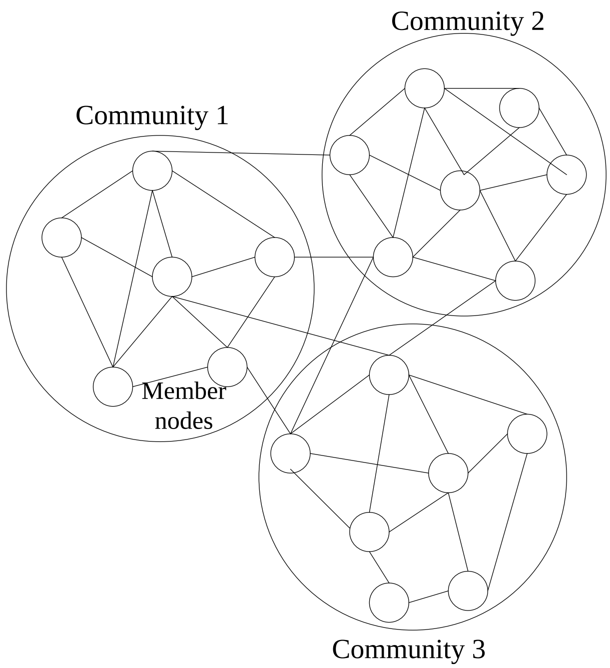

Figure 2. Social Attribute based Mobility Model (SaMob)

A Social Mobility Model (SMM) is always based on a social network model (SNM) that defines the structure of the relations between mobile users. Existing SMMs are tightly integrated with a specific SNM and cannot be changed. Thus, it might be difficult to choose the right SNM for a specific scenario. Moreover, the SNMs that are used in SMMs are quite simple and cannot evaluate the performance of the applications based on them. SNMs with more realistic properties are not used by existing SMMs. Existing mobility models also do not consider group mobility, such as the fact that people tend to move in groups due to their social bonding. Work done by Fischer D. et al. [3] introduces General Social Mobility Model (GeSoMo) as an attempt to take this into account. Their model receives a social network as an input and creates a social mobility model as output, which simulates mobility based on social relations. Authors compare the characteristics of GeSoMo to real measurements of human mobility and show that GeSoMo produces realistic mobility patterns. However, this mobility model does not consider both spatial and temporal features of a mobility model. Since people move or go to a place at a certain time for a specific reason, there is always a spatial-temporal correlation behind human mobility. Most human mobility models represent only spatial features (where and how they visit); only a few models consider temporal features (when they visit). Research conducted by Hong S. et al. [5] introduces a spatio-temporal mobility model (STEP) to eliminate the problem of not correlating the given temporal feature with the spatial feature. They demonstrate a correlation of temporal with spatial features through GPS experiments, which tracked the movement of 200 students in two university campuses.

As mentioned earlier, the contact-based networks are dependent on human mobility since the mobility patterns are significant to extract information from these networks which include not only spatial and temporal data but also relational and social aspects of people involved in the network. Thus, it is very important to design a mobility model that is simple but also sufficiently expressive and adjustable to different parameters. Work done by Zignani M. [14, 18] introduces Geo-CoMM, a geo-community-based mobility model that can reproduce the spatial, temporal and social features of human mobility from real mobility traces or datasets which are extracted using GPS. In this model, people move within a set of geo-communities where geo-communities (defined as locations frequently visited by a few people following speed, pause time and choice rules; statistical analysis is used to obtain the distributions of these data). People move following the Levy walk model inside a geo-community.

This method can also derive existing social relationships from traces by representing the system (i.e., node, geo-community) as a bipartite graph. The strength or weight of edges represents the strength of relationships among nodes. Simulation results demonstrate how the proposed model reproduces the statistical features of real dataset setting some parameters.

The mobility models and approaches we presented do not work in a large scale. The work done by Kosta S. et al. [8] introduces a novel mobility model for ad hoc networks, namely Small World in Motion (SWIM). This is a very simple, scalable and easily adjustable system which can be adapted to different scenarios and still accurately models them. SWIM generates synthetic traces that have the similar statistical properties of real traces in terms of their inter contact time, contact duration and contact frequency among pairs of nodes. Moreover, SWIM can generate social behavior among nodes and model networks with complex social communities, which are the base of the human mobility in real life. It can predict the performance of forwarding protocols of ad hoc network types, such as Epidemic, Delegation Forwarding, Spay and Wait, and BUBBLE. This is the first mobility model that works on a large scale and can evaluate the scalability property of these protocols.

The SWIM mobility model trades-off proximity and popularity, and distribution of waiting time; as a result, it is able to predict the performance of forwarding protocols. It models real life scenarios, such as whenever a node reaches a destination, it will decide how long to stay there, since in real life a person usually stays a long period of time in only a few places.

The mobility models which are presented here, and most other existing human mobility based network management (e.g., data dissemination) approaches, consider the parameters, inter-contact and contact distributions for contact analysis in opportunistic networks. Though these two parameters are important, Hossmann T. et al. [7] identifies that structural properties of contacts can also have a great impact on the performance analysis of network protocols of opportunistic networks. They introduce a contact graph - a graph theory approach to represent the contacts in mobile networks as a weighted graph, where the duration and frequency of contacts between a pair of nodes are represented as tie strength. The authors consider four mobility scenarios based on the number of nodes and origins and find that mobility is strongly modular, and has small world characteristics of short path length and high clustering coefficients.

The work done by Rhee I. et al. introduces the Levy walk mobility model [13] that imitates human walk patterns of people carrying mobile devices. Authors studied the statistical pattern of human walks within a radius of tens of kilometers on two university campuses, one metropolitan area and a theme park, and collected traces from 44 participants carrying GPS receivers for the duration of 1000 hours. Results of data analysis reveal that mobility patterns of the participants in outdoor environments have similar features to the Levy walks (i.e., flight and pause time distributions follow the truncated power law distributions). However, due to some geographical constraints such as roads, buildings and traffic flights, some of the mobility patterns are truncated, i.e., a slight deviation from the pure Levy walk occurs. The Authors also showed that the Levy walk has better performance than the Random Waypoint model (RWP) in MANET and worse performance than DTN.

Many of the mobility models that are presented exhibit the human movement characteristics. However, these methods do not consider clustering environment and the implementation of these methods are too complex. However, human beings have a significant clustering trend in real life; the more a given population are concentrated in a particular location, the stronger desire that a person who is a mover of their population will want to go to there. The work done by Zhang W. et al. [17] introduces a Mobility Model based on Location Attraction (LAMM). The proposed model utilizes the clustering or socializing feature/nature of human beings in real life. Using GPS traces of mobile users, the authors observe that the number of hot regions (where users visit more) is extremely stationary in an observation area. The pause position density within hot regions shows a trend with an exponential decline. Based on such movement characteristics authors designed LAMM that better depicts the mobility patterns of humans. However, this mobility model does not incorporate the heterogeneousness property. Thus, the work done by Hu L. and Dittmann L. introduce Heterogeneous Community-based Random Way-Point (HC-RWP) mobility model [9], which has several evaluative properties: node, space, time heterogeneousness and time periodicity. Simulation results demonstrate that HC-RWP captures heterogeneousness properties as well as statistical features (e.g., inter contact time, contact frequency) of real human mobility. In the HC-RWP approach, a set of nodes form a community which has the same home location. Nodes of the same community meet and stay in their home locations more frequently and nodes with different communities meet in their roaming locations less frequently. Moreover, the home locations of a node can change over time. For instance, people of a company meet more frequently in the company's restaurant and students meet more frequently in students' centre but both company workers and students might meet less frequently in shopping malls or train stations (roaming locations). Students also join in a company when they graduate and thus, change their home locations over a period of time. These scenarios are considered in designing the HC-RWP mobility model. However, HC-RWP while scalable does not support temporal and spatial correlations of mobility patterns.

IV. PROPOSED MOBILITY MODEL

This paper introduces the social and cultural attribute-based hybrid mobility model.

A. Building the Mobility Model

The input of the proposed mobility model will be data collected from individuals who participated in an event (e.g., conference, workshop) using the IEEE 802.15.4 or 802.11 communication protocols and devices. The participants are normally from different countries with different cultural backgrounds. The collected data includes demographic information (e.g., country, language) along with the number of times each participant is in contact with others. Based on the collected information, a contact graph, G (V, E) is created, where V is a set of participants and E is a set of edges (or contacts) between two participants. Each edge $\{u, v\}$ will have a number w that represents the number of times u and v were in contacts during a certain period of time.

Fig. 3 illustrates such a contact graph where participants are leveled as the alphabet A, B, C, D and an edge between two participants represents the strength of contacts using the weight w. For instance, the weight of the edge between nodes A and B is 10. Thus, this model allows grouping among the participants who have strong ties. Fig. 3 shows two groups of participants. The strength of contacts is greatly dependent on the demographic similarity of these human beings along with the spatial and temporal features. This is because a participant from a specific country and language would like to contact another participant from the same country and language. Thus, we would identify the similarity of other data (e.g., demographic) and their impact on building a contact graph and corresponding group structure. Similar features from the input data are used to identify and form a number of clustered features to investigate the impact of clustered features on the human mobility. For instance, features f1, f2, and f3 form a cluster and features f4 and f5 form another cluster.

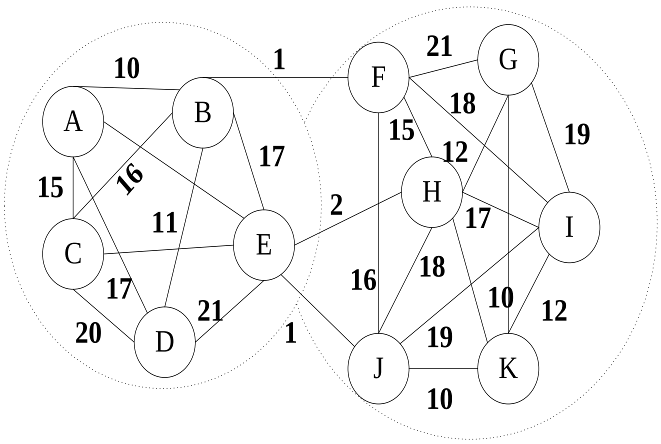

Figure 3: Contact graph and grouping

Then we create grouping of the participants using each feature. The feature for which we get the stronger community structure, i.e., a few groups each having a large number of participants, will have more impact on the human mobility. Similarly, the clustered features, {f1, f2, f3} or {f4, f5} for which we get stronger community structure will have more impact than others on human mobility. We use the widely used algorithm proposed by Newman and Girvan [19] to create the community structure in the human contact graph. In this algorithm, an edge which has the highest "betweenness" will be deleted recursively until a number of communities or groups are created.

Once groups or communities are formed we build the mobility model based on participant's social activity, which depends on social or cultural features. Let m be the number of participants communicating with each other, n be a number of clusters, each comprising a number of features that influences human mobility, $1 \le i \le n$. In the proposed mobility model, n = 2, i.e., only two clusters, one with demographic information (country of citizenship and residence, language) and another with professional information (affiliation, area of expertise).

The matching of a specific feature, $F_{i,j}$ e.g., language between two participants, P_{k1} and P_{k2} is represented as follows:

$$M_{F_{i,j}}(P_{k1}, P_{k2}) = \begin{cases} 1 & \text{if } F_{i,j} \text{ of } P_{k1} \text{ and } P_{k2} \text{ completely match} \\ 0 & \text{if no common } F_{i,j} \text{ value between } P_{k1} \,\&\, P_{k2} \\ \dfrac{l}{m} & \text{if } l \text{ among } m \text{ distinct values of } F_{i,j} \\ & \text{between } P_{k1} \text{ and } P_{k2} \text{ are common} \end{cases} \tag{1}$$

where $F_{i,j}$ denotes j-th feature of i-th cluster and $1 \le P_{k1}, P_{k2} \le m$

Now, the matching value of the feature $F_{i,j}$ among all participants can be represented by:

$$V_{F_{i,j}} = \sum_{k1=1}^{m} \sum_{k2=1}^{m} M_{F_{i,j}}(P_{k1}, P_{k2}), \quad k_1 \ne k_2 \tag{2}$$

The mean value of $V_{F_{i,j}}$ (between 0 and 1) for each participant is

$$\overline{V}_{F_{i,j}} = \frac{V_{F_{i,j}}}{m \times m} \tag{3}$$

We can map the number of contacts among the participants to the matching value $V_{F_{i,j}}$ of the feature $F_{i,j}$. We call this mapping the impact factor $I_{F_{i,j}}$ for a feature $F_{i,j}$ which is represented as follows:

$$I_{F_{i,j}} = \frac{V_{F_{i,j}}}{N_{F_{i,j}}} \tag{4}$$

$$N_{F_{i,j}} = \sum_{k1=1}^{m} \sum_{k2=1}^{m} C_{k1,k2}, \quad k_1 \ne k_2 \tag{5}$$

where $N_{F_{i,j}}$ is the total number of contacts and $C_{k1,k2}$ is the contacts between participants k_1 and k_2. The value of $N_{F_{i,j}}$ is greatly influenced by the temporal and spatial features. For instance, the participants with the same language and citizenship contact whenever they go to the conference venue based on their time schedule. The feature $F_{i,j}$ for which the value of $N_{F_{i,j}}$ is the highest will have more impact on human (or participants) mobility.

Now, we measure the matching value and impact factor of all features in each group and compare them to identify the group which has more influence on human mobility. Let us assume that the number of features in each group is f_i, where, $1 <= i <= n$ and $n = 2$ in the proposed model.

Thus, the total matching value of all features in each cluster, i can be represented as:

$$V_i = \sum_{j=1}^{f_i} \sum_{k1=1}^{m} \sum_{k2=1}^{m} M_{F_{i,j}}(P_{k1}, P_{k2}), \quad k_1 \neq k_2 \tag{6}$$

The mean value of V_i (between 0 and 1) of the matching value is:

$$\overline{V_i} = \frac{V_i}{f_i \times m \times m} \tag{7}$$

Similarly, the impact factor I_i of all features in each group i is represented as follows:

$$I_i = \frac{V_i}{N_{F_{i,j}}} \tag{8}$$

The group i, which has the highest impact factor, has more influence on human mobility. For instance, if the group with the language, citizenship and country of residence features has the highest impact factor, then it will have more influence on the human mobility. With this, we can find out if a cultural or professional feature as well as a clustered grouping of similar features, has a greater influence on human mobility.

B. Calculating New Location of a Participant

Let us assume that C is the number of communities and P_i is the number of participants in each community where $1 \leq i \leq C$. We can calculate $\overline{V_i}$ for the community i for each cluster of features (using Equation 7). If the matching value of a participant k_1 is $V_{k1} \geq \overline{V_i}$ and P_{ik1} participants have matching value greater than or equal to $\overline{V_i}$ the probability that P_{ik1} will contact another participant P_{ik2} ($V_{k2} \geq \overline{V_i}$) in the next time instant is given by:

$$\Pr(k1 \rightarrow k2) = \frac{V_{k2}}{P_{ik2}} \tag{9}$$

V. IMPLEMENTATION AND EVALUATION

The simulation was performed in order to evaluate the proposed model, or the impact of different social factors in human mobility model. The simulation parameters and respective values are presented in Table I.

In this simulation, 50 - 200 participants were randomly assigned to a location within a 300 x 300 meter^2 conference area. Each participant was assigned a number for representing their country, language, affiliation and studies. The authors considered that language and country are correlated, i.e., if a person is from India, one of her languages would be Hindi.

TABLE I. SIMULATION PARAMETERS AND THEIR VALUES

Parameter	Value
Network Size	300 x 300 meter^2
Number of Nodes	Maximum 200
Communication range	100 meters
Language	0 – 7
Country	0 – 6
Affiliation	0 - 4
Studies	0 – 5

Then, the participants will move around the conference area and connect with another participant based on (i) the matching value (Equations 1 and 2) and communication range of the device he/she is carrying. Then we identify the number of participants who connect to each other based on either language features/clusters or academic features/cluster, the number of links and the average node degree in each cluster. We compare all these metrics between language and academic clusters to determine which cluster has more impact on human mobility.

A. Real Data Traces

We use real data traces to validate the proposed mobility model. The data traces [20] were collected by others from the IEEE conference mentioned earlier. The data traces contain Bluetooth sighting by 70 students and researchers, carrying iMotes devices for four days (April 23 – 26, 2006). 20 stationary iMotes having longer radio range were placed throughout the conference area, e.g., lifts, bar, concierge.

Data traces contains the ID1 of the source iMotes that record the sighting, ID2 of the iMotes and external devices, e.g., smart phone, PDA that were seen, time when ID1 starts recording the sighting of ID2 and also the time the contact between ID1 and ID2 occurred before disconnecting. During the experiment, a questionnaire was filled up by the participants, which asked questions about personal background information, such as city and country of residence, citizenship, language, affiliation, and membership. Due to privacy, the information was provided as integer numbers instead of actual information. Table II shows the data traces we use in the proposed mobility model.

B. Grouping of Data Trace Information

The data trace contains social, cultural and professional information of a specific group of people at a conference. Their information was divided into two groups or clusters: (i) a language cluster: cultural information, which comprises mainly country of citizenship and language (ii) an academic cluster: professional information, which comprises their affiliation and area of expertise. The proposed mobility model compares the impact of the parameters or features of these two clusters on human mobility identified the cluster representing

TABLE II. REAL DATA TRACES FROM IEEE INFOCOM 2006

Source Node ID	Seen Node ID	Contact Count	Source Country	Seen Country	Source Nationality	Seen Nationality	Source Language	Seen Language	Source Study	Seen Study	Source Affiliation	Seen Affiliation
34	37	221	1	1	1	1	1,2	1, 2	35	1	1	1
76	66	148	15	15	16	16	14,1	14,1	36	36	24	32
39	46	128	3	3	3	25	5	7,1,5	3	3	3	3
44	41	122	17	2	2,5	1	24	1,2	40	2	28	19
45	64	119	3	3	27	11	26,1	11,1,5	46	12	10	10
72	87	116	14	14	14	14	22,1,15	15,1	19,33,34	19,47	23	23
82	77	113	9	9	2	12	3,1	12,1	14	16,14	11	11
25	22	107	5	5	4	7	5,1,14	8,5,1	18	26	13	5
64	45	106	3	3	11	27	11,1,5	26,1	12,	46	10	10
28	93	97	5	5	4	4	5,1,7	5,1	29,30,5	5	5	5
22	25	90	5	5	7	4	8,5,1	5,1,14	26	18	5	13
81	93	88	5	5	4	4	5,8,1	5,1	5	5	5	5
64	74	84	3	3	11	11	11,1,5	25,11	12	42,17	10	10
66	82	84	15	9	16	2	14,1	3,1	36	14	32	11
67	81	84	5	5	4	4	5,1,16	5,1,8	5	5	13	5
72	93	84	14	5	14	4	22,1,15	5,1	19,33,34	5	23	5
77	84	84	9	9	12	28	12,1	16,5,1	16,14	49	11	11

how the participants communicate with each other. We have also investigated the impact of any of any particular social or cultural factor which has significant influence on the clustering effects of participants who gathered together.

C. Simulation Result and Discussion

Fig. 4, 5, and 6 present simulation results of the proposed mobility model. We compare the impact of language and academic cluster for human mobility by varying the number of participants between 50 and 200.

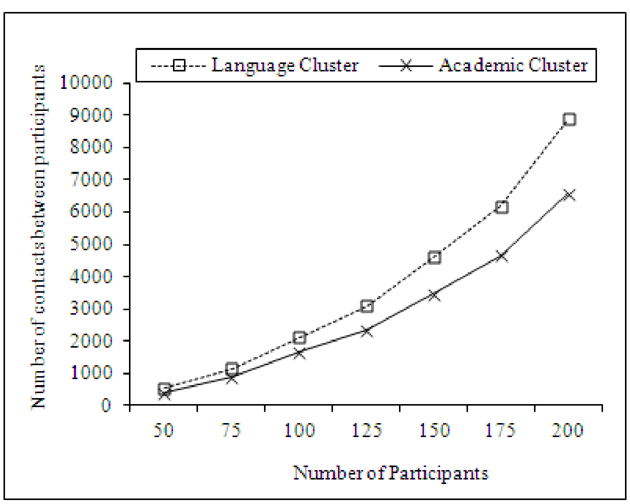

Figure 4. Number of contacts between participant based on Language and Academic features

Fig. 4 illustrates that the number of contacts or links that are created based on language features or clusters are larger than that created based on academic features. This is because the human beings have a greater tendency to move to a place where they find people of the same language and citizenship than the people of the same academic background. Thus, the number of participants that creates a community or a group based on the language feature will be based more on this factor than one which is based only on the academic feature (is illustrated in Fig. 5).

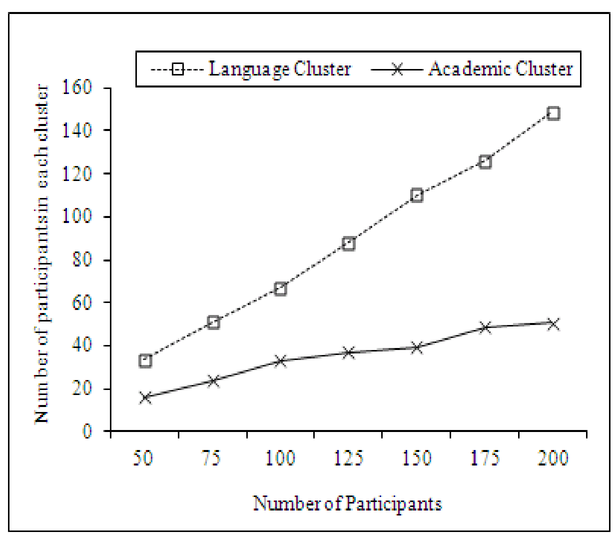

Figure 5. Number of participants in Language and Academic clusters

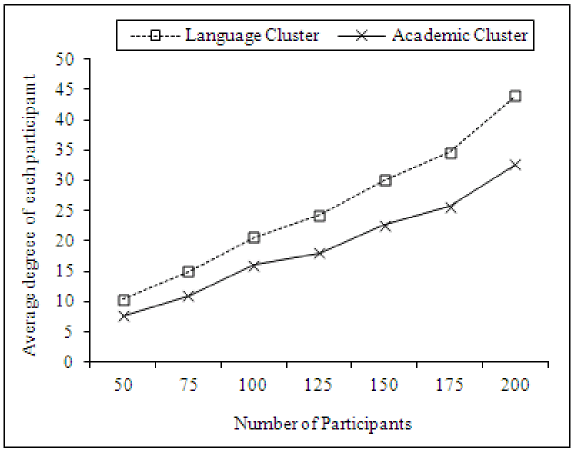

Figure 6. Average node degree of contact graph among participants for Language and Academic clusters

Similarly, Fig. 6 demonstrates that the average node degree of the contact graph created among participants is higher for contacts based on the language feature than for the academic feature. The simulation results match the real data traces since the observed number of contacts between two participants will be higher if they have the same language and country. Furthermore, the inter-contact time is lower and the contact duration is higher for the participants in the language cluster than those in the academic cluster.

VI. CONCLUSION AND FUTURE WORK

This paper introduces a hybrid human mobility model based on social/cultural/language diversity, using real data traces of IEEE INFOCOM 2006, that shows that language is the most influential factor of human mobility. Simulations results demonstrate that the synthetic data traces matched the real data traces which were obtained. However, the data traces represent human mobility for a particular scenario (conference), where people of related interest groups meet. For future work, the authors plan to use other real traces with temporal and spatial data to build temporal, spatial, social, cultural, and language based hybrid mobility models. In addition, we plan to work on a reference model with a data set for other researchers to use.

REFERENCES

[1] Cai J., Wu W., "Movement model for battlefield with confrontation characteristic," *Communications, 2008. APCC 2008. 14th Asia-Pacific Conference on*, pp.1-4, 14-16 Oct. 2008.

[2] Dmytro K., Chiara B., Marco C., Andrea P., "An arrival-based framework for human mobility modeling," *World of Wireless, Mobile and Multimedia Networks* (*WoWMoM*), *2012 IEEE International Symposium on a*, pp.1-9, 25-28 June 2012, doi: 10.1109/WoWMoM.2012.6263683.

[3] Fischer D., Herrmann K., Rothermel K., "GeSoMo - A general social mobility model for delay tolerant networks," *Mobile Ad hoc and Sensor Systems (MASS), 2010 IEEE 7th International Conference on*, pp.99-108, 8-12 Nov. 2010.

[4] Harri J., Filali F., Bonnet C., "Mobility models for vehicular ad hoc networks: a survey and taxonomy," *Communications Surveys & Tutorials, IEEE*, vol.11, no.4, pp.19-41, Fourth Quarter 2009.

[5] Seongik Hong, Kyunghan Lee, Injong Rhee, "STEP: A spatio-temporal mobility model for humans walks," *Mobile Ad hoc and Sensor Systems (MASS), IEEE 7th International Conference on*, pp.630-635, 8-12 Nov. 2010.

[6] Hossmann T., Spyropoulos T., Legendre, F., "A complex network analysis of human mobility," *Computer Communications Workshops (INFOCOM WKSHPS), 2011 IEEE Conference on*, pp.876-881, 10-15 April 2011.

[7] Karamshuk D., Boldrini, C., Conti, M., Passarella, A., "Human mobility models for opportunistic networks," *Communications Magazine, IEEE*, vol.49, no.12, pp.157-165, December 2011.

[8] Kosta S., Mei A., Stefa J., "Small World in Motion (SWIM)", *Modeling Communities in Ad-Hoc Mobile Networking. SECON 2010*, pp. 10-18.

[9] Liang Hu, Dittmann, L., "Heterogeneous Community-Based Mobility Model for Human Opportunistic Network," *Wireless and Mobile Computing, Networking and Communications, 2009. WIMOB 2009. IEEE International Conference on*, pp. 465 - 470, 12-14 Oct. 2009.

[10] Motahari, S., Hui Zang, Reuther, P., "The Impact of Temporal Factors on Mobility Patterns," *System Science (HICSS), 2012 45th Hawaii International Conference on*, pp.5659-5668, 4-7 Jan. 2012.

[11] Oztas B., Kurt, T., Anarim, E., "A survey of social based mobility models for ad hoc networks," *Wireless Communication, Vehicular Technology, Information Theory and Aerospace & Electronic Systems Technology (Wireless VITAE), 2011 2nd International Conference on*, pp.1-5, Feb. 28 2011-March 3 2011, doi: 10.1109/WIRELESSVITAE.2011.5940826.

[12] Papageorgiou C., Birkos K., Dagiuklas T., Kotsopoulos S., "An obstacle-aware human mobility model for ad hoc networks," *Modeling, Analysis & Simulation of Computer and Telecommunication Systems, 2009. MASCOTS'09. IEEE International Symposium on*, pp.1-9, 21-23 Sept 2009.

[13] Injong Rhee, Minsu Shin, Seongik Hong, Kyunghan Lee, Seong Joon Kim, Song Chong, "On the Levy-Walk Nature of Human Mobility," *Networking, IEEE/ACM Trans on*, vol.19, no.3, pp.630-643, June 2011.

[14] Zignani M., "Geo-CoMM: A geo-community based mobility model," *Wireless On-demand Network Systems and Services (WONS), 2012 9th Annual Conference on*, pp.143-150, 9-11 Jan. 2012.

[15] Jingxin Wang, Jian Yuan, Xiuming Shan, Zhenming Feng, Junwei Geng, Ilsun You, "SaMob: A Social Attributes Based Mobility Model for Ad Hoc Networks," *Innovative Mobile and Internet Services in Ubiquitous Computing (IMIS), 2011 Fifth International Conference on*, pp.444-449, June 2011.

[16] Hui Ye, ZhiGang Chen, ZuoQun Xia, Ming Zhao, "A Data Dissemination Policy by Using Human Mobility Patterns for Delay-Tolerant Networks," *Communications and Mobile Computing (CMC), 2010 International Conference on*, vol.1, pp.432-436, 12-14 April 2010.

[17] Wendong Zhang, Xiaolin Gui, Jian An, Jinghua Jiang, "Location Attraction Mobility Model for Mobile Ad Hoc Network," *Computer and Information Science (ICIS), 2012 IEEE/ACIS 11th International Conference on*, pp.83-87, May 30 2012-June 1 2012, doi: 10.1109/ICIS.2012.66.

[18] Zignani M., "Human mobility model based on time-varying bipartite graph," *World of Wireless, Mobile and Multimedia Networks* (*WoWMoM*), *2011 IEEE International Symposium on a*, pp.1-4, 20-24 June 2011.

[19] Newman M. E. J. and Girvan M. Finding and evaluating community structure in networks. Physical Review E, 69, February 2004.

[20] CRAWDAD – A Community Resource for Archiving Wireless Data at Darthmouth, http://crawdad.org/, accessed on November 2012.