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# Improving Node Popularity Calculation using Kalman Filter in Opportunistic Mobile Social Networks

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*Abstract*—**Opportunistic mobile social networks (OMSNs) exploit human mobility to physically carry messages to the destinations. Routing algorithms in these networks typically favour the most popular individuals (nodes) as optimal carriers for message transfers to achieve high delivery performance. The state-of-the-art routing protocol BubbleRap uses a cumulative moving average technique (called C-Window) to identify a node's popularity level, measured in node degree, in a time window. However, our study found that node degree in real-life OMSNs varies quickly and significantly in time, and C-Window moreover slowly adapts to this node degree changes. To tackle this problem, we propose a new method of node degree computation based on the Kalman-filter theory. Using simulation, driven by real human contact traces, we showed that our approach can increase BubbleRap's performance, in terms of delivery ratio and traffic (load) distribution fairness.**

***Keywords: node degree, cumulative moving average, Kalman-filter***

## I. Introduction

In recent years, opportunistic mobile networks (OMNs) have gained popularity in research and industry as a natural evolution from mobile ad hoc networks (MANETs). OMNs maintain the MANET's basic features of cost-efficiency and self-organization, as nodes still self-organize in order to build multi-hop message transfers without requiring any pre-existing infrastructure. However, they completely redesign the characteristics of networking protocols proposed in MANETs, making them able to support the absence of a stable path between pairs of nodes that wish to communicate. In these networks, forwarding is not "on the fly" since the relay nodes store the messages when no forwarding opportunity exits and exploits their mobility to increase message delivery probability. This forwarding paradigm is known as *store-carry-forward*, and in OMNs node mobility creates opportunities for communication; in contrast, in MANETs node mobility is viewed as a potential disruption. Moreover, OMNs are delay-tolerant in nature since contacts between nodes occur unpredictably because the node's movement is effectively random. Technological advances are leading to a world replete with mobile devices, such as cellular phones, notebooks and gadgets, thus paving the way for a multitude of opportunities for device contacts. Examples of OMNs include animal wildlife monitoring networks [1], vehicular networks [2], and mobile human (social) networks [3].

This paper focuses on opportunistic mobile social networks (OMSNs) (called social pocket switched networks in [3]), a specific scenario of OMNs that exploits contact between mobile devices carried by individuals to enable message forwarding. As the mobile devices are carried by humans, knowledge of social behaviour and structure can be one of the key information sources for designing and providing efficient and effective routing protocols. Moreover, the authors in [4,5,6] showed that humans tend to move in a way that is influenced by their social relations. Consequently, social-based routing algorithms, e.g. [7,8,9], use structural information of individuals in the social network to select optimal carriers for message transfers. In general, we can identify two main properties involved when social-aware routing algorithms make forwarding decisions, namely *social closeness* and *global popularity*. Social closeness exploits a strong (social) relation between two nodes to increase message delivery probability: during a node contact, if either the current node or the contacted node has knowledge of the message destination, the algorithm selects the encountered node as a carrier of the message if it is socially closer to the destination, e.g. the node is in the same community (social clique) with the destination. However, when the destination is unknown to both nodes, the routing algorithm routes the message to a more globally popular node.

This paper aims at improving node (global) popularity calculation in OMSNs. Our contribution in this paper is twofold: first, we confirm that in a real scenario of OMSNs, node popularity varies rapidly and significantly in time. Therefore, detecting a node's popularity level at a time is a non-trivial task in this setting. Indeed, properly identify an instantaneous node popularity is required to keep the routing algorithms' performances high. A prominent social-based routing algorithm in the literature, BubbleRap [7], uses a cumulative moving average technique (called C-window) to calculate a node's popularity level (measured in node degree) in a time interval (or time window). However, we show that the C-Window calculation slowly adapts to the node popularity changes and hence disregards the existence of the fast, significant variations of node popularity in real-life OMSNs. Our second contribution is therefore we propose a new method of OMSN node popularity computation based on the Kalman-filter theory [10]. In mobile communication networks, Kalman-filter has been used in [11,12] to achieve a more accurate

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## I. INTRODUCTION

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prediction of the evolution of the context of a host (mobile device), such as battery level, storage space and connectivity change rate. Our work, to the best of our knowledge, is the first one that applies Kalman-filter on node popularity calculation in OMSNs. Using simulation driven by real human contact traces, we furthermore show that our approach can increase BubbleRap's performance, in terms of delivery success ratio and traffic (load) distribution fairness.

The rest of the paper is organized as follows. In Section II, we discuss OMSN node popularity change characteristics. Our proposed method of node popularity computation based on the Kalman-filter theory is given in Section III. Section IV describes the performance improvement of BubbleRap when it applying our method in real-life OMSNs. Finally, Section V concludes the paper.

## II. Node Popularity Change Characteristics

In social network analysis (SNA), node popularity in a (social) network can be evaluated by a centrality metric. Centrality can be seen as a quantitative measure of the structural importance of a given node within the graph, e.g. the Freeman's centrality metrics [13], i.e. degree centrality, betweeness centrality and closeness centrality. Degree centrality, the simplest one, is defined as the number of links incident upon a given node. It is a local metric as it is only determined by the number of neighbours of the node. The other two are based on measuring shortest paths to quantify the relevance of a node. On the one hand, there is closeness centrality, which can be defined as the total geodesic (i.e. shortest path) distance from a given node to all other nodes. On the other hand, there is betweeness centrality that can be defined as the number of shortest paths passing through a given node. Both centrality metrics take into account the global structure of the network; therefore, their computations require complete network information, which is not normally available in the networks with very long transfer delays, such as OMSNs.

In OMSNs, the most popular individuals (hub nodes) can be seen as good candidates to be relay nodes for message transfers. In these networks, node popularity depends on a node's own social behaviour, which in turn depends on its sociability level or mobility pattern in the network. A higher sociability level or mobility rate results in a node that is more popular in the network and hence is a better candidate to act as an information carrier. In practice, this measure can be quantified by looking at metrics such as connectivity change rate [11,14] or the number of distinct nodes encountered in a given time interval [7]. In the literature, the latter is equal to the node degree centrality (or node degree in the graph theory) in an aggregated contact graph. Moreover, BubbleRap [7] uses the C-window technique for determining node degree in a time interval (or time window). This technique is a cumulative moving average that determines node $i$'s degree value in a time window $t$, denoted $\bar{d_i}(t)$, by calculating the node degree value averaged over all previous time windows as follows

$$\bar{d_i}(t) = avg(d_i(t-1),\ d_i(t-2), \ldots, d_i(0)) \qquad (1)$$

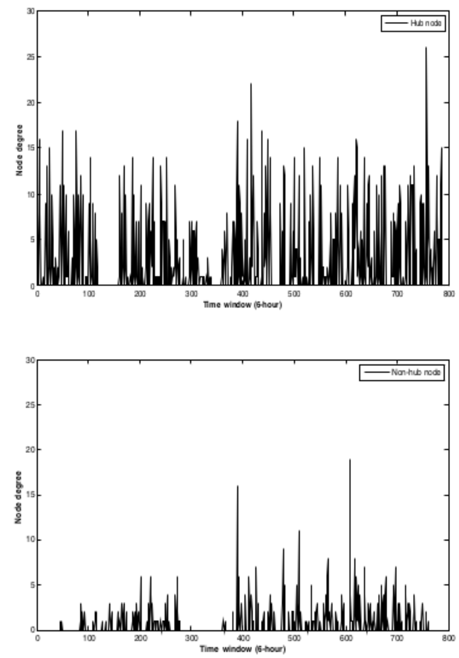



Fig. 1. The changes of popularity level (measured in node degree) of an illustrative hub node (upper) and non-hub node (lower) in Reality

However, our following investigation shows that node popularity in real-life OMSNs varies rapidly and significantly in time; it is therefore important to consider these characteristics when calculating a node's popularity level at a time.

In this study, we use a real human contact dataset, namely Reality [15]. This dataset captured academic activities of the students and staffs of Massachusetts Institute of Technology (MIT) over an academic year. In Fig. 1, we depict the changes of node popularity level, measured in node degree, of an illustrative hub node and non-hub node in Reality. Here, a node's degree value in a time window is calculated as the number of distinct nodes encountered aggregated in a 6-hour time interval: we choose this calculation since we agree with the authors of BubbleRap in that human daily life intuitively can be divided into 4 main periods: morning, afternoon, evening and night - each almost 6 hours.

Fig. 1 shows that the popularities of both nodes vary rapidly in time, with the significant changes mainly occur in the hub node. Furthermore, as we show later in Section IV.B, the C-window calculation (1) fails to capture this such changes of node degree in OMSNs. This therefore motivates us to improve the C-window method of BubbleRap, and eventually we propose the Kalman-filter prediction technique [10] used to estimate a node's degree value at a given time interval. Kalman-filter was originally developed in the control systems theory. The technique is the minimum-variance state estimator for linear dynamic systems with Gaussian noise. Even if the noise is non-Gaussian, Kalman-filter is the best linear estimator [16].

## III. Node Popularity Calculation using Kalman-Filter

We now discuss a new approach of OMSN node degree computation using the Kalman-filter prediction technique. In this method, node degree values in all previous time windows are considered as a discrete time series. Subsequently, they are treated as inputs to the Kalman-filter system in order to estimate a node's degree value in the current time window. We now show our estimation model derived based on the Kalman-filter theory. We use a state space model [17] to describe our problem. A state space model for a time series $Y_t$ is composed of the following two scalar equations. The first one is the observation equation as follows

$$Y_t = X_t + W_t \,, \qquad t = 1,2,\ldots$$

with $W_t = WN(0, Q_t)$ is white noise with zero mean and variance $Q_t$. The second one called the state equation is the following

$$X_{t+1} = X_t + V_t \,, \qquad t = 1,2,\ldots$$

with $V_t = WN(0, R_t)$. We assume that $V_t$ is uncorrelated with $W_t$ and the initial state $X_1$ is uncorrelated with all of the noise terms $V_t$ and $W_t$. We now briefly describe the derivation of the Kalman-filter prediction for this state space model. With the notation of $P_t(X)$, we refer to the best linear predictor of $X$ in term of $Y$ at time $t$ as follows

$$P_t(X) \equiv P(X \mid Y_0, Y_1, Y_2, \ldots, Y_t)$$

From [18], it is possible to prove that the one step predictor $\hat{X}_t \equiv P_{t-1}(X_t)$ and its covariance $\Omega_t = E\left[(X_t - \hat{X}_t)^2\right]$ are determined by these initial conditions

$$\hat{X}_1 = P(X_1 | Y_0)$$

$$\Omega_1 = E\left[\left(X_1 - \hat{X}_1\right)^2\right]$$

and this recursive equation

$$\hat{X}_{1+1} = \hat{X}_t + \frac{\Omega_t}{\Omega_t + R_t}(Y_t - \hat{X}_t) \qquad (2)$$

with

$$\Omega_{t+1} = \Omega_t + Q_t - \frac{{\Omega_t}^2}{\Omega_t + R_t}$$

We eventually use (2) to calculate a node's popularity value at time window $t$ as follows: given the previous observed node degree value at time window $t-1$, denoted $d_{t-1}$, and the predicted node degree value at time window $t-1$, denoted $\hat{d}_{t-1}$, the node degree value at time window $t$, $\hat{d}_t$, is estimated using (2).

TABLE I. The simulation main parameters

| Simulation Parameters | | |
|---|---|---|
| Mobility scenario | Reality | Sassy |
| Number of nodes | 100 | 25 |
| Simulation time | 16981816 sec (~ 196 days) | 6413284 sec (~ 74 days) |
| Msg. creation interval | ~ 12 msgs/h | ~ 6 msgs/h |
| Node buffer size | 20 MB | |
| Message TTL | 7 days | |
| Message size | 10 kB | |

## IV. Performance Evaluation

### A. Simulation Setup

To investigate the performance of our proposed method of node degree computation, we consider BubbleRap routing [7]. BubbleRap was developed based on two aspects of society: *community* and *popularity*. Community is defined as a subset of nodes with stronger connections among themselves than towards other nodes. It usually implies a social group, e.g. friends, family, co-workers etc. Consequently, in this algorithm each node has global popularity in the entire network and also local popularity within its community. When either a node or its contact is in the message destination's community, local popularity is considered in the forwarding decision. However, when the destination is unknown to both nodes, the algorithm selects the contacted node as a carrier of the message if its global popularity is higher than the current node's. BubbleRap uses node degree to quantify both node global and local popularities. Here, node degree is determined as a count of the unique nodes seen by the node during a certain time window. A cumulative moving average (C-window) technique is subsequently used to smoothing the value of node degree.

In this paper, we only focus on improving node global popularity calculation in OMSNs: we improve BubbleRap by applying Kalman-prediction on the computation of node global popularity (hereafter, we call this improved algorithm *Bubble-Kalman*). In consequence, to calculate node local popularity in a given community we follow BubbleRap that uses C-window. Finally, we compare the delivery performance of BubbleRap with that of Bubble-Kalman in real-life OMSNs.

We implement both algorithms using the ONE simulator [19], an event-driven simulator for opportunistic networks. The main simulation parameters for the evaluation are given in TABLE 1. The number of nodes and the length of simulation time vary depending on the node mobility scenario. For the simulation's node mobility scenario, we use real human contact data traces, namely Reality [15] and Sassy [20]. In Reality, 100 smart phones were deployed among the students and staffs of MIT over period of 9 months. It captured academic activities in the campus over an academic year. In contrast, the Sassy trace was collected using a mobile sensor network with TMote invent devices carried by 25 participants from the University of St. Andrews for period of 74 days. For community detection, we use the *k*-clique distributed community detection algorithm proposed by Hui *et.al* [21] for both BubbleRap and Bubble-Kalman. For the *k*-clique parameters, we choose $k$=5 and a familiar threshold $T_{th}$=250ks for Reality, and $k$=3 and $T_{th}$=3ks for Sassy.

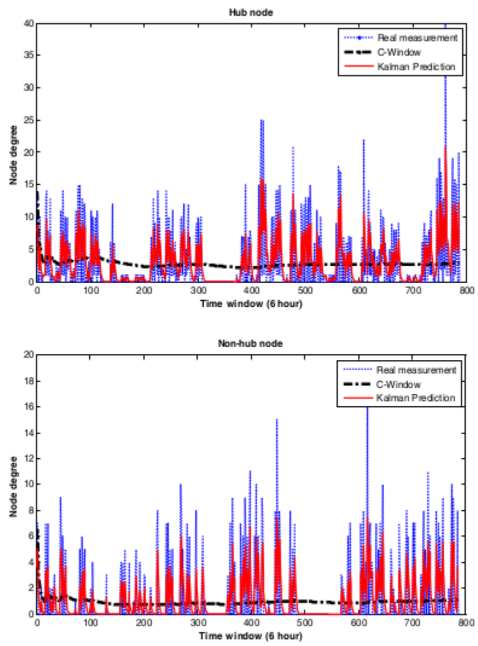



Fig. 2. Time series for node degree values of an illustrative hub node (upper) and non-hub node (lower) in Reality, comparing the measured value, the C-window estimate, and the Kalman prediction values

For performance analysis, we use several evaluation metrics as follows:

a) **Delivery ratio**: the ratio of the number of messages successfully delivered divided by the total number of message created.

b) **Delivery delay**: the time between the creation of a message and the delivery of the message to its final destination.

c) **Message overhead ratio**: the ratio of the number of overhead messages to the number of messages successfully delivered. The total number of overhead messages is calculated as the total forwarded (copy) messages minus the total number of messages successfully delivered.

d) **GINI index**: this measure [22] of statistical dispersion calculates the inequality among values of a frequency distribution. In this paper, the GINI index gauges the traffic distribution fairness level in the network, i.e. an index of 0 means that the traffic is distributed evenly, and a value of 1 indicates only a single node processes all the network traffic.

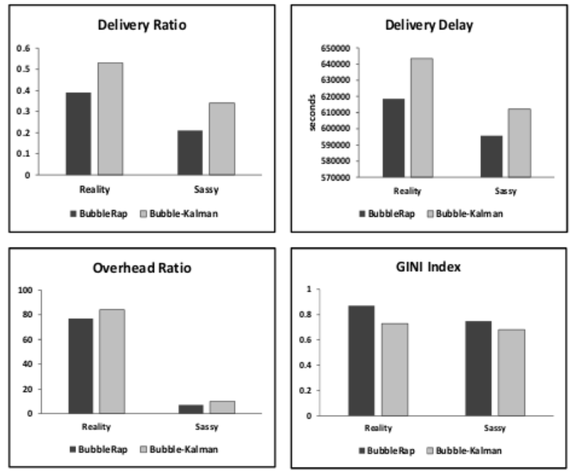


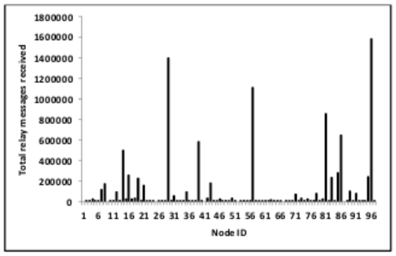

Fig. 3. Delivery performances of BubbleRap and Bubble-Kalman in Reality and Sassy

### *B. Simulation Results*

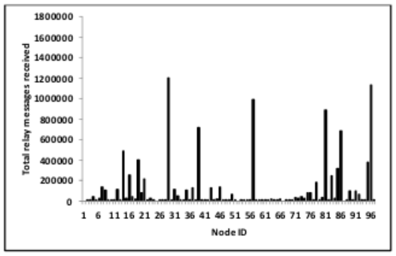
We now discuss the simulation results of BubbleRap and Bubble-Kalman in two node mobility scenarios, Reality and Sassy. Initially, in Fig. 2 we depict the degree value of an illustrative hub node and non-hub node in a time series in Reality. For each time window (i.e. a 6-hour time interval), a node degree level is calculated using real measurement ($d_t$), C-window ($\bar{d}_t$) and Kalman-prediction ($\hat{d}_t$). It is clear from the figure that Kalman-prediction captures the variations of node degree values and hence provides better estimates of the node popularity in a given time window than C-window (i.e. $\hat{d}_t$ is a better estimator of $d_t$ than $\bar{d}_t$). C-window slowly adapts to the node popularity changes and thus disregards the existence of the rapid, significant variations of node degree, particularly in the most popular node.

We next consider the delivery performance of BubbleRap and Bubble-Kalman. In Fig. 3, we show the performance evaluation results of BubbleRap and Bubble-Kalman in Reality and Sassy. The evaluation metrics described in Section IV.A are considered in this performance analysis.

In Fig. 3, we see that Bubble-Kalman produces in a better message delivery ratio in both Reality and Sassy. Moreover, the improvement in delivery ratio is not associated with an increase in delivery cost (measured by the overhead ratio), and Bubble-Kalman manages this cost as well as BubbleRap. On the other hand, Bubble-Kalman can improve the BubbleRap's traffic distribution fairness (measured by GINI index) in both node mobility scenarios and the decrease in GINI index is more obvious in Reality. However, Bubble-Kalman increases the average delivery delay beyond that of BubbleRap in both scenarios. Bubble-Kalman's worse delivery latency performance is related to the reduced traffic at the most popular node (hub nodes). As shown in Fig. 3 (GINI Index), Bubble-Kalman has a lower GINI index than BubbleRap's; hence it produces a better traffic (load) distribution.




(a) BubbleRap




(b) Bubble-Kalman

Fig. 4. Total relay messages received by each node in Reality for BubbleRap (upper) and Bubble-Kalman (lower)

Even though the decrease in GINI index seems insignificant in both mobility scenarios, in fact the total traffic processed by hub nodes is reduced considerably. For instance, in Fig. 4(a) and 4(b) we show the total relay messages received by each node in Reality for BubbleRap and Bubble-Kalman, respectively. It is clear that Bubble-Kalman is able to significantly reduce the total relay traffic in a few hub nodes. However, when Bubble-Kalman successfully redirects much of the traffic away from the hub nodes, this leads to a significant increase of the delivery latency in the network (Fig. 3 (Delivery Delay)). Since the message deliveries in the network now prefer to use alternative paths (rather than shortest-paths via hub nodes), this leads to the increase of the overall network delivery latency. Thus we see a trade-off between traffic (load) distribution fairness and delivery delay performance.

In the literature, several papers highlight an important issue of unbalanced traffic (load) distribution in OMSNs: the works in [23,24,25,26] have identified that favouring higher popularity nodes contributes to the unfair traffic distribution in the network. The authors of SimBet [8] found that use of (ego) betweeness centrality alone as the routing metric yielded traffic overloading at the central (hub) nodes. In this paper, on the other hand, we show that Bubble-Kalman is able to reduce traffic in a few hub nodes, leading to the increase in traffic distribution fairness in the network; however, this increases delivery latency beyond that of BubbleRap. Given that OMSNs are assumed to be delay-tolerant, this increase in delivery time is not considered significant; instead, the reduced load on the most popular nodes, reflected in the improved GINI index, represents a substantial improvement in the performance of the network.

## V. Conclusions

This paper presents two important contributions in the area of node popularity computation in OMSNs: firstly, we confirmed that in real-life OMSNs node popularity changes rapidly and significantly in time. Moreover, the C-window calculation of BubbleRap is insensitive to this such node degree changes. Secondly, we therefore proposed the Kalman-prediction technique used to identify a node's global popularity level at a time interval. We next applied our method on BubbleRap (called Bubble-Kalman hereafter). We showed that Bubble-Kalman achieves better delivery ratio and increases traffic distribution fairness, reducing the GINI index below that of BubbleRap, but at the cost of high delivery latency beyond that of BubbleRap. Given that OMSNs are assumed to be delay-tolerant, this increase in delivery time represents an acceptable trade-off compared to the improved fairness in the network and the reduced resource consumption in the most popular nodes.

## References


[1] P. Juang, H. Oki, and Y. Wang, "Energy-Efficient Computing for Wildlife Tracking: Design Tradeoffs and Early Experiences with Zebranet", Proc. 10th Intl. Conf. on Arch. Support for Prog. Lang. and Op. Sys, San Jose, CA, USA, 2002, pp. 96-107.

[2] Y. Sabry, A. Mtibaa and K.A. Harras, "Opportunities in Vehicular Opportunistic Networking", Proc. Intl. Wireless Comm. and Mobile Comp. Conf., Paphos, Cyprus, 2016, pp. 818-823.

[3] A.K. Pietilainen and C. Diot, "Social Pocket Switched Networks", Proc. 9th INFOCOMM Wkshp, Rio de Janeiro, 2009, pp. 1-2.

[4] V. Borrel, F. Legendre, M. Amorim, and S. Fdida, "SIMPS: Using Sociology for Personal Mobility", IEEE/ACM Trans. on Nets, vol. 17, no. 3, pp. 831-842, 2009.

[5] T. Hossmann, T. Spyropolous, and F. Legendre, "A Complex Network Analysis of Human Mobility", Proc. IEEE Conf. on Comp. Comm. Wkshp, Shanghai, China, pp. 876-881, 2011.

[6] M. Conti and M. Kumar, "Opportunities in Opportunistic Computing", IEEE Computer J., vol. 43, no. 1, pp. 42-50, 2010.

[7] P. Hui, J. Crowcroft, and E. Yoneki, "BUBBLE Rap: Social-based Forwarding in Delay Tolerant Networks", IEEE Trans. on Mobile Comp., vol. 10, no. 11, pp. 1576-1589, 2011.

[8] E.M. Daly and M. Haahr, "Social Network Analysis for Information Flow in Disconnected Delay-Tolerant MANETs", IEEE Trans. on Mobile Comp., vol. 8, no. 5, pp. 606-621, 2009.

[9] A. Mtibaa, M. May, C. Diot, and M. Ammar, "PeopleRank: Social Opportunistic Forwarding", Proc. 29th Conf. on Info. Comm., San Diego, CA, pp. 111-115, 2010.

[10] R.E. Kalman, "A New Approach to Linear Filtering and Prediction Problem", J. Basic Eng., vol. 82, no. 1, pp. 35-45, 1960.

[11] M. Musolesi and C. Mascolo, "CAR: Context-Aware Adaptive Routing for Delay-Tolerant Mobile Networks", IEEE Trans. on Mobile Comp., vol. 8, no. 2, pp. 246-260, 2009.

[12] P. Costa, C. Mascolo, M. Musolesi, and G.P. Picco, "Socially-Aware Routing for Publish-Subscribe in Delay-Tolerant Mobile Ad Hoc Networks", IEEE J. on Select. Areas in Comm., vol. 26, no. 5, pp. 748-760, 2008.

[13] L.C. Freeman, "Centrality in Social Networks: Conceptual Clarification", Social Networks, vol. 1, no. 3, pp. 215-239, 1979.

[14] E. Yoneki, P. Hui, and J. Crowcroft, "Distinct Types of Hubs in Human Dynamic Networks", Proc. 1st Wkshp. on Soc. Net. Sys., Glasgow, UK, pp. 7-12, 2008.

[15] N. Eagle and A. Pentland, "Reality Mining: Sensing Complex Social Systems", Personal and Ubiquitous Comp., vol. 10, no. 4, pp. 255-268, 2006.

[16] D. Simon, "Kalman Filtering with State Constraints: A Survey of Linear and Nonlinear Algorithms", IET Control Theory and Apps., vol. 4, no. 8, pp. 1303-1318, 2010.

[17] J. Durbin and S.J. Koopman, "Time Series Analysis by State Space Methods", 2nd ed., Oxford Univ. Press, UK, pp. 19-23, 2012.

[18] P.J. Brockwell and R.A. Davis, "Introduction to Time Series and Forecasting", Springer-Verlag, pp. 23-31, 2002.

[19] A. Keranen, J. Ott, and T. Karkkainen, "The ONE Simulator for DTN Protocol Evaluation", Proc. 2nd Intl. Conf. on Simult. Tools and Tech., Rome, Italy, pp. 55-62, 2009.

[20] G. Bigwood, D. Rehunathan, M. Bateman, T. Henderson, and S. Bhatti, Crawdad Dataset st_andrew/sassy, available online at http://crawdad.org/st_andrew/ sassy, May 2013.

[21] P. Hui, E. Yoneki, S.Y. Chan and J. Crowcroft,"Distributed Community Detection in Delay Tolerant Networks", Proc. 2nd ACM/IEEE Intl. Wkshp. on Mobility in the Evolving Int. Arch., Kyoto, Japan, pp. 1-8, 2007.

[22] C. Gini, "On the Measure of Concentration with Special Reference to Income and Statistics", Colorado College Pub., General Series, no. 208, pp. 73-79, 1936.

[23] J.M. Pujol, A.L. Toledo, and P. Rodriguez, "Fair Routing in Delay Tolerant Networks", Proc. IEEE Intl. Conf. on Comp. Comm., Rio de Janeiro, Brazil, pp. 837-845, 2009.

[24] B. Soelistijanto, "Impact of Social-Aware Forwarding on Traffic Distribution in Social Opportunistic Networks", Proc. IEEE Reg. 10 Symp., Bali, Indonesia, pp. 13-18, 2016.

[25] B. Soelistijanto, "The Efficiency-Fairness Trade-Off of Social Rank Based Forwarding in Social Opportunistic Networks", Proc. IEEE Asia Pacific Conf. on Wireless and Mob., Bandung, Indonesia, pp. 113-119, 2016.

[26] V. Erramilli, M. Crovella, A. Chaintreau and C. Diot, "Delegation Forwarding", Proc. the 9th ACM Intl. Symp. Mobile Ad Hoc Netw. and Comp., Hong Kong, China, pp. 251-260, 2008.

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