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## Periodicity Detection of Node Behaviour in Opportunistic Mobile Social Networks

Bambang Soelistijanto
Department of Informatics
Sanata Dharma University
Yogyakarta, Indonesia
b.soelistijanto@usd.ac.id

Elisabeth Kusuma Adi Permatasari
Department of Informatics
Sanata Dharma University
Yogyakarta, Indonesia
permatasari_erma@yahoo.com

***Abstract*—The recent rise of networks that rely on human mobility, such as opportunistic mobile social networks (OMSNs), has prompted the need for methods that detect the periodic patterns of node movements. Knowledge of the periodicity of node behaviour is essential to design effective and efficient network protocols in such networks. Node behaviour in OMSNs is typically characterized by the node contact patterns. In fact, node connections in these networks occur intermittently, resulting in sparse contact data. Consequently, the traditional periodicity detection methods, e.g. the FFT periodogram and autocorrelation, that favour complete, regularly-sampled time-series data are unsuitable in this setting. In this paper, we exploit the Lomb-Scargle periodogram, initially designed to handle incomplete or irregular sampling data, to identify node behaviour periodicity in OMSNs. Using simulation driven by real human contact traces, we show that the technique is able to accurately detect the behaviour periodicity of majority nodes in the network, even for those with a high level of sparsity contact data.**

***Keywords—periodicity detection, sparse contact data, the Lomb-Scargle Periodogram***

### I. Introduction

As a natural evolution of mobile ad-hoc networks (MANETs), opportunistic mobile networks (OMNs) [1] have gained popularity in research and industry in recent years. While MANETs require pre-existing paths to enable message transfers, OMNs are able to support communication between pairs of nodes in the absence of stable paths between them. Unlike MANETs that consider node mobility is a potential disruption, message delivery in OMNs relies on unpredictable node contacts, resulting in a higher delivery delay than that of MANETs. Message delivery in OMNs is therefore delay-tolerant in nature. Although other realisations of OMNs exist, human-based opportunistic mobile networks (also referred to as *pocket-switched networks* [2] or *opportunistic mobile social networks* (OMSNs) [3]) are the most prolific. A key factor in the proliferation of these systems is the rapid adoption of mobile devices, such as smart phones, gadgets, and laptops.

In general, the key challenge in OMSNs is choosing the best message carriers to enable message delivery in a high success rate within a short delivery time. By taking a user-centric approach to networking, knowledge of human behaviour and structure can be one of the key information sources for designing effective and efficient routing protocols in OMSNs. For instances, the social-aware forwarding algorithms proposed by Daly *et al*. [4] and Hui *et al.* [5] use two social structure information, namely social-rank (betweeness and degree centralities, respectively) and social-closeness (similarity and community, respectively), as the forwarding metrics to choose the most likely message carriers in the network. Furthermore, it has already been proven that the idea about people moving in a random manner is no longer valid nowadays [6]. Instead, it turns out that human tend to have repetitive behaviour, such as (social) activities that they perform periodically to fulfill their social needs, e.g. going to offices on weekdays or meeting friends in coffee shops on weekends. Hui *et al.* [5], when designing the BubbleRap routing algorithm, divided human daily life into 4 main periods: morning, afternoon, evening, and night – each almost 6 hours. Moreover, Williamson *et al*. [7] argued that considering the periodic patterns of node mobility in making routing decisions can improve the network delivery performance. Indeed, accurately identify the periodic patterns of node behaviour is essential to design more efficient routing algorithms in OMSNs.

There are several methods in the literature that can be utilized to identify the periodicity of time series data, such as the FFT periodogram [8] and autocorrelation [9]. These conventional methods typically favour complete, uniformly-sampled data in time order. However, this requirement is no longer valid in the case of OMSNs. In these networks, node behaviour is commonly characterized by the node encounter patterns. Due to the intermittent contacts in OMSNs, it is difficult to obtain node connection information in each time bin of regularly-sampled time series data. Consequently, the majority of the time bins are filled up with value of '0', resulting in sparse time-series contact data. Moreover, even though the traditional methods are able to detect node contact periodicity, these strategies consume a lot of memory space of OMSN nodes to save a large number of data of '0'. Clearly, this situation is critical in mobile communication networks, since the network nodes possess a very limited storage or buffer capacity. Detection on the periodicity behaviour of nodes in OMSNs is therefore a challenging task.

In this paper, we propose the Lomb-Scargle periodogram [10] to calculate node behaviour periodicity in OMSNs. This technique is a well-known algorithm for detecting and characterizing periodic signals in incomplete or unevenly-

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*by* Soelistijanto Bambang

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Bambang Soelistijanto
Department of Informatics
Sanata Dharma University
Yogyakarta, Indonesia
b.soelistijanto@usd.ac.id

Elisabeth Kusuma Adi Permatasari
Department of Informatics
Sanata Dharma University
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permatasari_erma@yahoo.com

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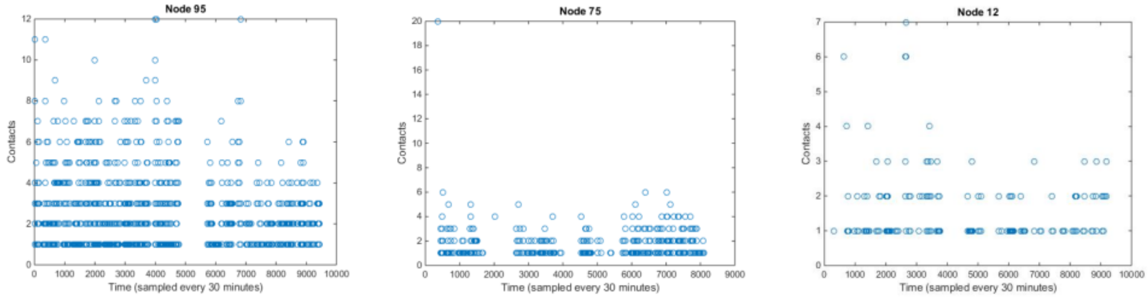


Fig. 1. Reality scenario: Node-contact time bins equally-sampled every 30 minutes

sampled time series data. In our case, however, the Lomb-Scargle periodogram identifies the periodic patterns of sparse, uniformly-sampled time series contact data in OMSNs. Moreover, the time bins with value of 0 can be considered as none (*NaN*) in this algorithm. As a result, these values do not need to be stored in nodes' storage, leading to the significant reduce of the memory usage. In this study, we use two real human contact datasets, namely Reality [11] and Haggle [12]. We consider the former dataset as the long-term mobility case, while the latter as the short-term case.

The rest of the paper is structured as follows. In Section II, we discuss the characteristics of node contact data in real-life OMSNs. Periodogram techniques for detecting the periodicity of time-series contact data is presented in Section III. Subsequently, Section IV describes the performance evaluation of the Lomb-Scargle periodogram compared to the FFT periodogram in detecting node behaviour periodicity in the OMSNs. Finally, Section V concludes the paper.

## II. Characteristics of Node Contacts in OMSNs

In this section, we discuss the characteristics of node contact patterns in real-life OMSNs. We consider two real human contact datasets, namely Reality and Haggle. In each dataset, we choose 3 nodes with different level of activeness in the network, e.g. the most active node, moderately active node, and the least-active one.

### A. *Reality Mining Dataset*

The Reality Mining contact dataset [11] captured the activities of students and staffs of MIT during one academic year. There were 97 participants, comprising both undergraduate and postgraduate students and laboratory staffs. The experiment was performed around 10 months at the MIT campus. Using the ONE simulator [13], for each network node we regularly record the number node connections in every a 30-minute time interval. Eventually, this creates uniformly-sampled time-series contact data.

From the dataset, we found that the most active node, node 95, completed 3486 contacts with other nodes throughout the simulation time. However, when the contact data are sampled uniformly in every 30 minutes on the node's connections to the peers, there are more than 85% of the time bins with no connection data. In other words, only 15% of the time-series contact data are available to be used to detect the node's behaviour periodicity. Specifically, we depict in Fig. 1 the records of encounters of node 95, 75 and 12, which represent the most active, quite active, and the least active nodes, respectively, in Reality. The figure shows that the most-active node has the lowest level of data sparsity, roughly 75%. In contrast, the least-active node possesses the highest level of sparsity, namely 97%. In between the two nodes, the quite active node, node 75, has 83% level of data sparsity.

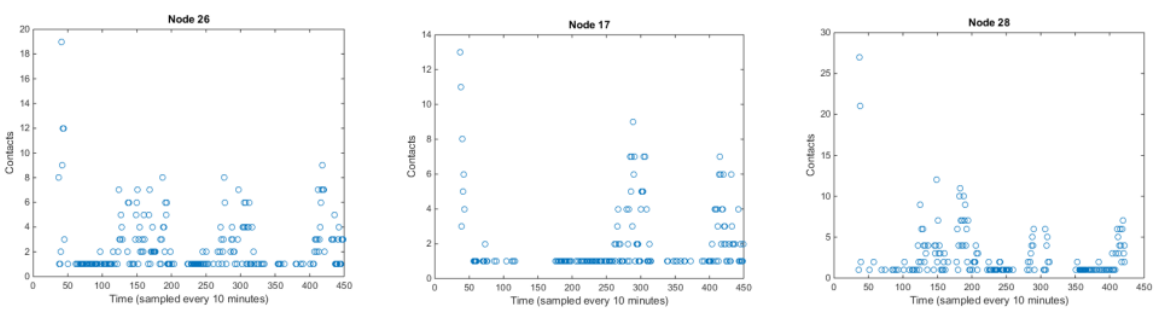


Fig. 2. Haggle scenario: Node-contact time bins equally-sampled every 10 minutes

### *B. Haggle Infocomm Dataset*

The second dataset we consider in this study is Haggle [12], which represents the short-term real human mobility case. This contact trace was taken during IEEE Infocomm 2005 conference in Grand Hyatt Miami participated by 41 persons and lasted for 3 days. For each node in the dataset, using simulation we repeatedly capture the number of node contacts in every a 10-minute time interval throughout the simulation time.

In Fig. 2, we show the records of the number of contacts of illustrative nodes in the dataset, namely node 26, 17 and 28. Node 26 is considered as the most active node in the network. In this node, the missing data of the node contacts in the time bins reach more than 53%. On the other hand, node 17 and 28 have roughly, respectively, 61% and 69% time bins with no connection data, i.e. values of "0".

## III. Periodicity Detection Techniques in OMSNs

To identify the periodic patterns of node behaviour in OMSNs, in each node total contacts are recorded into time series data sampled in equally spaced time intervals. Based on the signal processing theory, it is needed to calculate power spectral density (PSD) of any time series data for periodicity detection. To enable this computation, signals from time domain must be converted into frequency domain. The calculated PSD represents the power of its possible frequency. Since the period of a signal is the inverse of its frequency, the dominant periodicity of the signal would be the frequency with the strongest PSD. This spectral analysis method estimation is also known as periodogram.

The widely used periodogram is based on FFT, such as Discrete Fourier Transform (DFT) [14]. The normalized DFT of a sequence $x(n), n = 0,1, \dots, N-1$ can be defined as follows:

$$x\left(f_{\frac{k}{N}}\right) = \frac{1}{\sqrt{n}} \sum_{n=0}^{N-1} x(n) e^{-\frac{j2\pi kn}{N}} \tag{1}$$

$X$ is the DFT of a sequence $x(n)$, where the subscript $k/N$ denotes the frequency captured by each coefficient. To find the dominant frequency, the power of each frequency must be calculated. Finally, the periodogram $P$ can then be calculated as:

$$P\left(f_{\frac{k}{N}}\right) = \left\| X\left(f_{\frac{k}{N}}\right) \right\|^2 \qquad k = 0,1, \dots, \left\lceil \frac{N-1}{2} \right\rceil \tag{2}$$

In the case of OMSNs, uniformly sampling on intermittently node contacts in real-life OMSNs produces sparse time series contact data as previously described in Section II. Since the storage capacity of mobile devices is very limited, it is important to sensibly use the nodes' memory space. We consequently propose to remove all the time bins containing zero contact, resulting in incomplete time series data. As a result, the FFT periodogram is no longer able to identify the periodic patterns of the node's time-series contact data. For such scenario, we instead use the Lomb-Scargle periodogram [10] to detect the periodicity behaviour of OMSN nodes. Lomb-Scargle periodogram is formally defined as follows:

$$P_X(\omega) = \frac{1}{2} \left\{ \frac{\left[\sum_{n=1}^{N} y(t_n) \cos(\omega(t_n - \tau))\right]^2}{\sum_{n=1}^{N} cos^2(\omega(t_n - \tau))} + \frac{\left[\sum_{n=1}^{N} y(t_n) \sin(\omega(t_n - \tau))\right]^2}{\sum_{n=1}^{N} sin^2(\omega(t_n - \tau))} \right\} \tag{3}$$

where $\tau$ is defined as:

$$\tan(2\omega\tau) = \frac{\sum_{n=1}^{N} \sin(2\omega t_n)}{\sum_{n=1}^{N} cos(2\omega t_n)}$$

## IV. Performance Analysis of the Periodogram Techniques in OMSNs

In this section, we discuss the performance evaluation of the periodogram methods mentioned in Section III in OMSNs. Initially, we investigate the accuracy of the Lomb-Scargle periodogram with incomplete time series contact data compared to the FFT periodogram with complete data in identifying the periodic patterns of node behaviour in real-life OMSNs, namely the Reality and Haggle human mobility scenarios. Subsequently, we examine the extend of data sparsity level to which the Lomb-Scargle periodogram is still able to work properly.

In Fig. 3, we depict the periodicity detection results of nodes in Reality when the two periodogram techniques are applied. We again consider the three nodes in Reality mentioned in Section II, namely node 95, 75 and 12, which represent the most active, moderately active, and the least active nodes, respectively. We see from the figure that the FFT periodogram is surely able to detect almost the same values of periodicity of all the nodes' behaviour roughly ≈ 7 days, even though they have a different level of activeness in the network. Moreover, this weekly periodicity in the long-term scenario is in line with the findings from some studies in social network analysis [15,16] that human tend to have a weekly pattern in their mobility or social activities. Despite its benefit, however, the FFT periodogram requires complete time series contact data to be able to work accurately. This means that a single node should keep all its encounter data throughout the simulation time, leading to quickly deplete the node's memory space. To address this issue, we then remove the (unnecessary) time series contact data containing values of '0' from the node's memory and next apply the Lomb-Scargle periodogram to identify the node's periodic patterns. From Fig. 3, we notice that the method successfully identifies the behaviour periodicity of node 95 and 75 as high as that of the FFT periodogram, which is a weekly cycle. However, the Lomb-Scargle periodogram is ineffective to detect the periodic pattern of node 12, which is the least-active node in Reality that has the highest data sparsity level at nearly 97%.

We next consider the short-term node mobility scenario in this investigation. Fig. 4 illustrates the detected periodicities of nodes in the Haggle dataset. From the figure, we observe that the Lomb-Scargle periodogram is able to detect node periodicities as nearly accurate as the FFT calculation in node 26 and 17, namely an hour cycle. Obviously, the Haggle dataset captured the human movement during a conference that typically has hourly-scheduled activities. However, as in the Reality dataset,

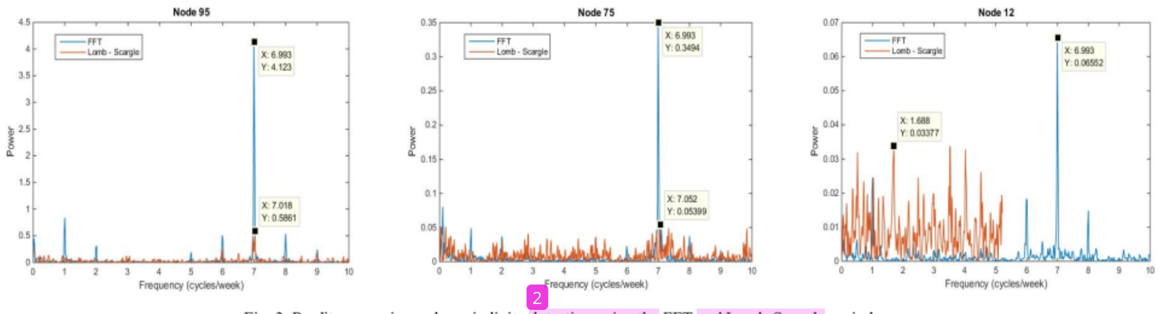


Fig. 3. Reality scenario: node periodicity detection using the FFT and Lomb-Scargle periodograms

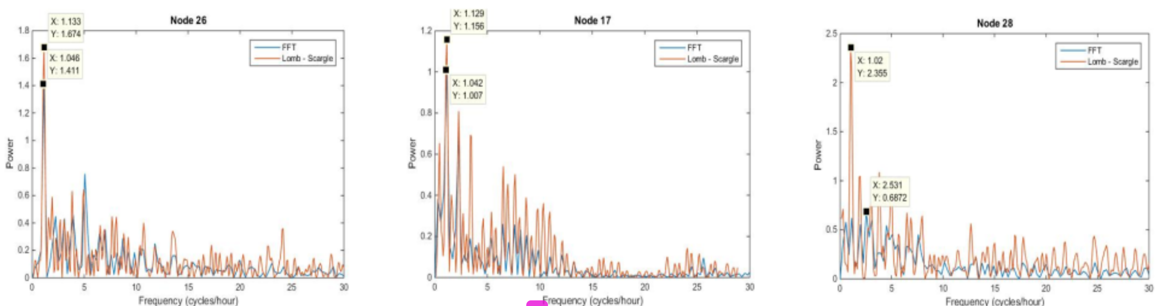


Fig. 4. Haggle scenario: node periodicity detection using the FFT and Lomb-Scargle periodograms

the Lomb-Scargle periodogram is again unsuccessful in correctly detecting the behaviour periodicity of the least-active node in Haggle, node 28, that possesses the data sparsity level at 69%.

Finally, we discuss the performance of the Lomb-Scargle periodogram in real-life OMSNs in terms of the length of contact data traces. As shown above, the length of time series contact data directly affects the upper-bound of data sparsity level where the Lomb-Scargle periodogram is able to work properly. The technique tends to have a better performance if it is applied to long contact data datasets; for example, in Reality the Lomb-Scargle periodogram successfully identifies the nodes' periodic patterns in a higher level of contact data sparsity, around 80% - 85%. On the other hand, in the case of short contact datasets, the algorithm is unsuccessful to accurately detect nodes' behaviour periodicities at a lower data sparsity level: in the Haggle dataset, it fails after the contact data sparsity level exceeds 64%.

In mobile communication networks, such as OMSNs, the memory capacity of mobile devices has become one of the crucial issues. In regard to this, we believe that the Lomb-Scargle periodogram is preferable to be used for detecting node behaviour periodicity in such networks, despite its limitation. Furthermore, to overcome the method's drawback, we argue that the Gossip protocols [1[illegible]] can be exploited to broadcast a node's periodicity value to all other nodes in the network until they have the same knowledge of the nodes' behaviour periodic patterns. Nevertheless, it needs further study to confirm our idea.

## V. Conclusions

In this paper, we have investigated the Lomb-Scargle periodogram for identifying node behaviour periodicity in OMSNs. We consider two distinct real human mobility scenarios, both the long-term and short-term contact data traces. We identify that the Lomb-Scargle periodogram is suitable for calculating node behaviour periodicity in OMSNs, since its accuracy reaches as high as that of the FFT periodogram. In addition, the method is more efficient as it requires less time-series data, leading to save more memory space of OMSN nodes. Furthermore, the Lomb-Scargle periodogram gives more tolerance to the data sparsity level in the long-term mobility scenario. In this case, the method is able to accurately detect the periodicity behaviour of the nodes having a relatively high data sparsity rate.

For future work, we will improve the performance of the Lomb-Scargle periodogram in detecting node behaviour periodicity, particularly in the least active nodes. We also need to investigate the use of the Gossip protocol to distribute node periodicity information to all nodes so that they eventually share the common knowledge of the periodicity behaviour of the nodes in the given network.

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