Selective Sensing Framework for Opportunistic Mobile Phone Sensing Networks

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***Abstract*—The rise of opportunistic mobile phone sensing paradigm is due to ubiquitous mobile phones usage. Optimisation of battery energy consumption and achieving required spatial coverage of sensing area are important issues under opportunistic mobile phone sensing networks. Human mobility enable collection of mobile phones sensor data and sensing area coverage by forming communication network with surrounding neighbors devices (mobile phones). This paper proposes a human mobility based selective sensing framework called as HWSS (Human Walk based Selective Sensing) for sensor data collection in opportunistic mobile phone sensing networks. In proposed HWSS method, mobile phones are selected for sensing task based on users current and predicted future locations and sensing overlap area. The proposed HWSS method is compared with non-selective sensing method (NSS), where all mobile nodes are allowed for sensing during sensor data collection process, in an given application area. The simulation results show that compared to NSS method proposed HWSS method achieves reduction in energy consumption and required spatial coverage.**

***Index Terms*—Energy Consumption, Human Walk, Mobile Phones, Sensing area Coverage, Sensors**

I. Introduction

Mobile phones or smart phones which are usually carried by humans are coming with different types of scalar and multimedia sensors. For a mobile phone, sensors may be embedded externally or inbuilt, includes accelerometer, gyroscope, magnetometer, digital compass, temperature, light, proximity, barometer, humidity, heart rate, SpO2 (peripheral capillary oxygen saturation), camera, microphone and GPS (Global Positioning System) [1], [2]. Mobile phones are also come up with different types of communication technologies like 2G/3G/4G and near field communications (Wi-Fi, Bluetooth and RFID (Radio-frequency identification) [1], [2].

Mobile phone sensing applications include urban monitoring [3], [4], [5], environment monitoring, traffic monitoring [6], health care monitoring [7], intelligent transportation, disaster management [8], [9], mass education and social networking [3], [10], [9].

Human mobility enables collection of mobile phone sensor data by forming network with other device (mobile phones) in their communication range for sensing task. There are numerous open issues and research challenges to build up efficient mobile phone sensing network applications using embedded sensors and communication resources. Efficient usage of battery power, spatial and temporal sensing area coverage are challenging research issues in mobile phone sensing. Opportunistic and dynamic human mobility nature and their activities affect the performance of mobile phone sensing networks [11]. In opportunistic mobile phone sensing, mobile phones come in contact with other mobile phones and devices opportunistically [11].

For continuous environmental sensing applications using mobile phone sensors, consider high density of mobile phone users scenario, there is more possibility of spatial and temporal sensing area overlap. Mobile phone resources will be shared by many applications running on it. Sensing applications should not drain battery power and affect other applications running on it. Ensuring required minimal energy consumption and required spatial and temporal coverage of sensor data are fundamental issues in mobile phone sensing.

This paper refers to human mobility based selective sensing for efficient mobile phone sensor data collection in opportunistic sensing networks. Levy walk (LW) mobility model which depict the statistical properties of human walk patterns is considered for evaluation of proposed work. Reference [12], [13], [14], [15], [16], [17] explore LW mobility model.

Formation of communication network between mobile phones for sensing task requires regular lookup for neighbors, processing and exchange of messages, security and trust protocols. Hachem *et al.* [18] discusses reducing number of participatory users plus improving coverage by assuming that users are aware of their path. Sheng *et al.* [19] presents collaborative mobile phone sensing using cloud network. They also assume that mobile phone users path is known in advance.

In opportunistic mobile sensing applications, where users visit in the vicinity of application region is not frequent or dynamic in nature, prediction of users current location, velocity, movement direction, future location, duration of stay using mobile phone sensors is preferable [20] [21], [12], [22], [23], [24]. There is need to analyse the impact of unpredictable and opportunistic nature of human mobility on energy consumption, spatial and temporal coverage on mobile phone sensing applications.

This paper considers opportunistic mobility nature of mobile phone users and analyses the impact of dynamic human movements and patterns on energy consumption and sensing area coverage by considering proposed selective sensing method.

In proposed work, current and predicted future locations of mobile phone users used for selecting mobile phones to perform sensing task. There are many references [20], [21], [22] which explain how mobile phone users movement velocity, direction and angles can be obtained by using sensors like accelerometer, magnetometer, gyroscope and GPS in outdoor and indoor locations. In this paper, we assume that mobile phones use any method to calculate or to obtain their velocity, direction and angle of movement. The proposed work is compared with non-selective mobile phone sensing task, where all the mobile phones are involved in sensing and sending their sensed data to dedicated destination. The proposed selective sensing method achieves required spatial coverage and also shows reduction in energy consumption for mobile phone sensing activity.

The remainder of this paper is organized as follows. Section II describes system model for the proposed work. Section III gives description of proposed selective sensing algorithm for opportunistic mobile phone sensing. Section IV discusses evaluation of simulation results and Section V concludes the paper.

II. System Model

This section provides the description of models used for the development of proposed selective sensing framework for opportunistic mobile phone sensing networks.

Let A be the area of application, which consists of p number of mobile phone users. Mobile phones are also termed as mobile phone users or mobile nodes. For performance analysis of proposed work LW mobility model given in [14] is used. Mobile nodes are categorised into two types. One is mobile sensing ms nodes, which are embedded with GPS for getting location co-ordinates and other application related sensors. Another type of mobile nodes are called as volunteer mobile vm nodes, which are embedded with GPS and may or may not come with other application related sensors.

Let ms_i represent i^{th} mobile sensing node, where $i = 1, 2, ...n$. and let vm_c represent c^{th} volunteer mobile node, where $c = 1, 2, ...m$ and n+m=p.

Let r_j be the sensing range of j^{th} sensor which is attached to i^{th} ms node, where $j = 1, 2, ...k$. We consider disk model for sensing range. Let t_j be the sampling interval of j^{th} sensor. When a mobile node moves in a straight line path with constant velocity cv and without pause or change of direction, then t_j for non-overlap sensing coverage with respect to j^{th} sensor is given by [25]:

$$t_j = 2 * \frac{r_j}{cv} \tag{1}$$

Let average or preferred human walk velocity be hwv. Under LW mobility model equation (1) is given by [25]:

$$t_j = 2 * \frac{r_j}{hwv} \tag{2}$$

III. Description of Proposed Selective Sensing Framework

It is assumed that a Dedicated Base Station (DBS) is responsible for sensor data collection from all the vm nodes and has dedicated control and sensor data collection channel. It is considered that vm nodes are programmed to send and receive query from a Dedicated Base Station (DBS). DBS broadcast query to vm nodes requesting their current location. Based on the reply from vm nodes, DBS selects specific vm node in the required application region. Multiple vm nodes can be selected but there should not be any overlap between the communication range of vm nodes for considered application time.

On receiving the command and information from DBS selected vm nodes initiate sensor data collection task with ms nodes. The pseudocode for collecting sensed data from ms nodes is given in Algorithm 1. For simplifying the performance analysis of proposed work under human mobility model, we assume collection of single sensor data from ms nodes.

For given simulation duration T, total number of sensor data collection iterations R is given by equation (3), where t_j is the sampling interval of a considered sensor (equation (2-3)). The proposed sensor data collection algorithm given in Algorithm 1 is repeated for every t_j duration until given time T. At the start of each iteration I where $I = 1, 2, ..., R$, vm computes eligible ms nodes for sensing task. The brief description of each step (Algorithm 1) is given in following subsections.

$$R = \frac{T}{t_j} \tag{3}$$

Algorithm 1 :Pseudocode for sensor data collection from ms nodes

1: **for** $I \leftarrow 1, R$ **do**
2: vm broadcast req_{info} packet to ms nodes.
3: ms nodes reply by sending requested data to vm through $replay_{info}$ packet.
4: vm computes the eligible ms nodes for sensing task and broadcast req_{sense} packet.
5: Selected ms nodes transmit sensed data within time assigned by vm.
6: **end for**

A. Broadcasting req_{info} packet

The selected vm node from DBS broadcasts req_{info} packet to ms nodes. In general, req_{info} packet consist of $[addr_{vm}, I, cur\_loc_{vm}, req\_addr_{ms}, req\_curr\_dir\_info, req\_sensor\_info, req\_velo]$. $addr_{vm}$, I and cur_loc_{vm} indicates vm node address, sampling iteration number and current vm node location respectively. req_addr_{ms}, $req\_curr\_dir\_info$, req_sensor_info and req_velo represents address of ms, direction related sensors information, other sensors information (sensor type and range), and current velocity. These are the parameters required by vm to select the eligible ms nodes for sensing task.

B. Sending $reply_{info}$ packet by ms nodes

On receiving broadcasted req_{info} packet, ms nodes compute required data which are specified by vm node and reply by sending $reply_{info}$ packet. $reply_{info}$ packet consists of $[addr_i, I, (xc_i, yc_i), curr\_dir\_info_i, \{sensor\_type_j, r_j\}, curr\_velo_i]$.

C. Broadcast req_{sense}

On receiving $reply_{info}$ packet from ms nodes which are sent within some t_{parm} time, vm computes the eligible ms nodes. The pseudocode for selecting eligible ms nodes for sensing task is given Algorithm 2.

Algorithm 2 :Pseudocode for selection of ms nodes

```
compute current overlap between ms nodes
compute future overlap between ms nodes
if (current overlap between any pair of ms nodes > π*r_j^2/3
and predicted future overlap > π*r_j^2/1.6) then
    remove any one ms node and mark another ms node
    as eligible node
else
    Mark both the ms nodes as eligible nodes
end if
```

For simulation of proposed work, direction of LW mobile nodes is calculated from their location traces.

Let (xc_i, yc_i) and (xp_i, yp_i) be the current and previous location co-ordinates at time t_2 and t_1 respectively where $t_1 < t_2$. Equation (4) gives the general formula for calculating direction angle of any i^{th} ms node.

$$\phi = \tan(yp_i - yc_i, xp_i - xc_i) \tag{4}$$

General equation to calculate future location co-ordinates for i^{th} ms node at given time t_f is given in equation (5), where $t_f > t_1$.

$$\begin{aligned} xf_i =& xc_i + curr\_velo_i * t_f * cos(\phi) \\ yf_i =& yc_i + curr\_velo_i * t_f * sin(\phi) \end{aligned} \tag{5}$$

By using current location, calculated future location and sensor range r_j of ms nodes, vm node calculate overlap sensing area between each and every pair of ms nodes. For any pair of ms nodes, if sensing area overlaps between them is greater than 33% when current location is considered and greater than 62% for predicted future location, then any one of ms is marked as non-eligible and another node is considered as eligible sensing node. If sensing area overlap between any pair of ms nodes is greater than 62% for predicted future location, then any one of ms is marked as non-eligible and another node is considered as eligible sensing node. After finding the eligible nodes and non eligible nodes vm broadcast req_{sense} packet. req_{sense} packet consists of information like eligible, non-eligible ms node id's of corresponding I^{th} sampling iteration, t_j and time limit to send back the sampled sensor data. By declining the assignment of sensing task to non-eligible ms nodes, overall sensing area overlap and energy consumption for proposed method is reduced.

D. Transmission of Sensor Data

It is assumed that some amount of time $t_{outrange\_node}$ (equation (6)) is spent by vm node after broadcasting req_{sense} packet to collect sensed data from ms nodes. Let ls and vm_{range} be the speed of light and vm node's communication range respectively. Within $t_{outrange\_node}$ time, if a ms node has not transmitted its sensor data, then it is assumed that the node has moved out of communication range of vm node.

$$t_{outrange\_node} > 2 * \frac{vm_{rage}}{ls} + t_j \tag{6}$$

IV. Simulation Results and Discussion

To simplify the performance analysis of proposed work, it is assumed that base station chooses a random vm node, which is within the range of 100 meters from center of application area A at time t_{vm}. It is assumed that within t_{start} $(t_{vm} < t_{start})$ time base station completes selection of vm node and sends the required information to start the mobile phone sensor data collection task. At time t_{start} selected vm node start sensor data collection routine (Algorithm 1.). The preferred human walk velocity hwv is $\approx$ 1.0 m/s [26].

For all ms nodes, sensor range is assumed to be 20 meters. Other considered simulation parameters are given in Table 1. Term NSS is used to represent non-selective sensing which allows all the ms node for sensing. In order to represent proposed human walk based selective sensing method we use term HWSS.

For given A, T, and p values, proposed mobile phone sensing method is analysed in terms of average units of energy consumption and spatial coverage (sensing area coverage). Better performance is needed in terms of reduction of energy consumption and also in terms of required spatial coverage.

Energy consumption and sensing area coverage is calculated for every iteration. For proposed method, energy consumption and sensing area covergae is represented by $HWSS\_E_I$ and $HWSS\_cov_I$ respectively. For NSS method, energy consumption and sensing area coverage is represented by NSS_E_I and NSS_cov_I respectively.

Let λ_HWSS_I and λ_NSS_I be the total number of sensor data samples sent to vm node from mobile nodes by HWSS and NSS methods respectively at I^{th} iteration.

Then non-overlap sensing coverage area for HWSS and NSS methods is given by equation (7) and (8) respectively.

$$HWSS\_nv\_cov_I = \pi * r_j^2 * \lambda\_HWSS\_I \tag{7}$$

$$NSS\_nv\_cov_I = \pi * r_j^2 * \lambda\_NSS\_I \tag{8}$$

For considered sensing methods, if their sensing coverage is greater or equal to respective non-overlap sensing coverage then the method is acceptable, i.e, considered sensing method has achieved required spatial coverage.

$$HWSS\_cov_I \geq HWSS\_nv\_cov_I \tag{9}$$

$$NSS\_cov_I \geq NSS\_nv\_cov_I \tag{10}$$

We assume one unit of energy is consumed for sensing (both GPS and sensor) and sending a sensor sample by a mobile

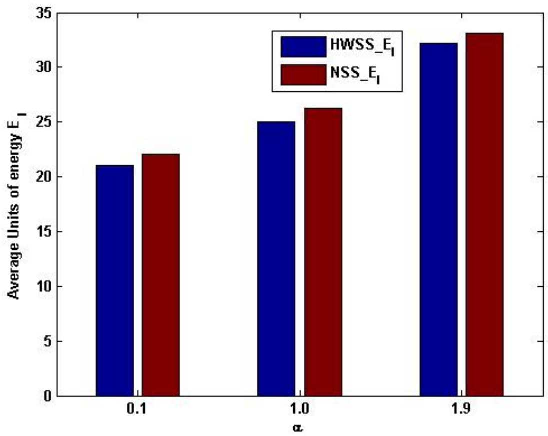

Fig. 1. Energy Consumption

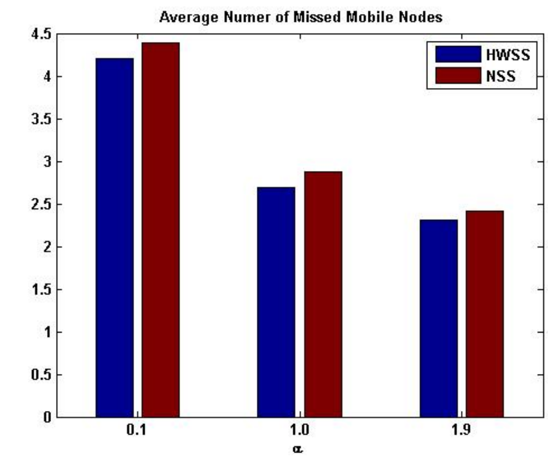

Fig. 2. Average number of missed mobile nodes

node. Therefore, total energy consumed for proposed and considered sensing method is equal to the respective total number of sensor samples received by vm in I^{th} iteration.

$$HWSS\_E_I = \lambda\_HWSS\_I \tag{11}$$

$$NSS\_E_I = \lambda\_NSS\_I \tag{12}$$

First the impact of velocity of mobile nodes on energy consumption and sensing area coverage is analysed for both the proposed HWSS and NSS methods. Birand *et al.* [15] explore dynamic graph properties under LW mobility model. As LW mobility parameter α value decreases, $(0 < \alpha < 2)$, mobile networks become more dynamic and vice-versa [15]. For analysing the performance of proposed work α in LW mobility model is set to 0.1, 1.0 and 1.9 $(0 < \alpha < 2)$ for generating low, high and medium speed ms nodes respectively. Table 2 show average velocity of mobile nodes. For this considered simulation parameters are given in Table 1.

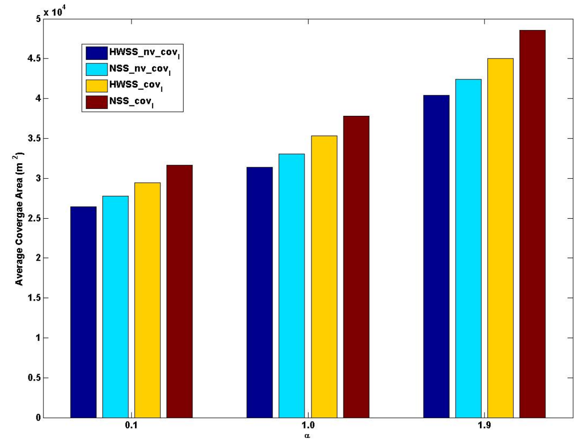

Fig. 3. Sensing Area Coverage

Figure 1 and 3 show average energy consumption and average sensing area coverage for different values of α. The simulation duration T is set to one hour, which is long enough to run many iterations. Other considered simulation parameters are given in Table 1. Dynamic network topology, i.e., when $\alpha = 0.1$, increases missing rate of mobile nodes (mobile nodes moving out of vm node range), thereby reducing number of sensor samples sent to vm node. Therefore when mobile phone nodes velocity is high i.e., for $\alpha = 0.1$ mobile nodes show very low coverage and energy consumption compared to $\alpha = 1.0$ and $\alpha = 1.9$ (Fig. 1 and Fig. 3). Low velocity mobile nodes lead to decrease in missing rate of mobile nodes (Fig. 2), as their incoming and outgoing rate within the application region is very slow. Therefore, when mobile phone nodes velocity is low i.e., for $\alpha = 1.9$ mobile nodes show very high coverage and energy consumption compared to $\alpha = 1.0$ and $\alpha = 0.1$ (Fig. 1 and Fig. 3). When mobile phone nodes velocity is equal to normal human walk velocity i.e., for $\alpha = 1.0$ mobile nodes show coverage and energy consumption in between to $\alpha = 0.1$ and $\alpha = 1.9$.

For proposed HWSS method, there is reduction of energy consumption (Fig. 1) for all the considered values of α. Because ms node are selectively chosen such that there should be less overlap between them. Both the sensing methods have achieved respective required sensing coverage area (Fig. 3). NSS covers much extra area then required and also energy consumption. In Fig. 3 the proposed HWSS method has also crossed required NSS method non-overlap sensing area coverage i.e., $HWSS\_cov_I > NSS\_nv\_cov_I$. In each sensor data collection iteration I, simulation results show reduction in energy consumption for HWSS method. Even a single percent reduction of energy consumption for each iteration will save a lot overall network energy in long run of mobile phone sensing applications. Combining the results of Fig. 1 and Fig. 3, proposed HWSS method show better performance in terms of reducing energy consumption of mobile nodes and also

TABLE I
SIMULATION PARAMETERS

Simulation Area A	2000m*2000m
p	1000 nodes
Simulation duration	1 hours
Flight parameter α	1, 1.9, 0.1
Pause parameter β	1.0
Average flight length	5-2000m
Pause time	10-60 seconds
hwv	1 meter/second
Location sample interval t_{ls}	1 second
(future location time) t_f	13 seconds
t_{vm}	15^{th} sec
t_{start}	16^{th} sec
vm and mn nodes range	200m
Range of sensor	20
Assumed datarate	100 kbps
req_{info}, $reply_{info}$, req_{sense} packet size	100 bytes
Each mn nodes sensor data size at each iteration	200 bytes

TABLE II
SIMULATION PARAMETERS

α	average velocity (m/s)
0.1	2.1
1.0	1.3
1.9	0.4

achieving required sensing coverage.

V. CONCLUSION

Human mobility plays an active role in improving the performance of mobile phone sensing applications, if their mobility characteristics are analysed and incorporated. This paper presents an human mobility based selective sensing framework called as HWSS for sensor data collection in opportunistic sensing networks. For the given network and applications parameters the proposed HWSS method show reduction in energy consumption and also achieves required spatial coverage. Our future work involves extending the proposed selective sensing to include multiple sensor data collection for ubiquitous mobile sensing applications. The future scope also involves analysing the computation and communication (varying geographical features and network link constrains) complexities involved in experimental implementation of proposed work.

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