Novel Sampling Algorithm for Human Mobility-Based Mobile Phone Sensing

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***Abstract*—Smart phones or mobile phones enabled with global positioning system (GPS), different types of sensors, and communication technologies have become ubiquitous application development platform for Internet of Things (IoT) and new sensing technologies. Improving sensing area coverage, reducing overlap of sensing area, and energy consumption are important issues under mobile phone sensing. This paper presents human mobility-based mobile phone sensors sampling algorithm. Human mobility patterns and geographical constraints have an impact on performance of mobile phone sensing applications. The real-outdoor location traces of volunteers, collected using GPS-enabled mobile phones are used for performance analysis of proposed work. The proposed mobile phone sensor sampling algorithm considers velocity of human mobility as an important parameter for improving sensing area coverage and reduction of energy consumption. To an extent overlap between sensing area coverage is allowed to overcome, the reduction of sensor data samples caused by spatial regularities of human mobility. The performance is analyzed and evaluated by considering general regular sampling and proposed sampling method for mobile phone sensing activity. The results show that for normal human walking velocity (<1.5 m/s) proposed mobile phone sensor sampling algorithm performs better in terms of sensing area coverage and reduction of battery energy consumption for mobile phone sensing activity.**

***Index Terms*—Global positioning system (GPS), human mobility, Levy walk, mobile phone sensing, sensor sampling, spatial coverage.**

I. INTRODUCTION

HUMAN mobility patterns and geographical constraints have an impact on the performance of mobile phone sensing applications, specifically on mobile phone sensing coverage and energy consumption. It is necessary to validate the performance of mobile phone sensing algorithms in real-world environment. This paper extends mobile phone sensors sampling algorithm proposed in paper [1] by considering real human location trace data. Human carried smart phones are becoming ubiquitous application development platform for Internet of Things (IoT) and new sensing paradigms such as participatory sensing, crowd-sourced sensing, opportunistic sensing, and human-centric sensing [2]–[5]. Latest smart phones are coming with different types of sensors such as camera, microphone, global positioning system (GPS), compass, gyroscope, temperature, humidity, barometer, and accelerometer embedded with them [2]–[4]. Mobile phones are also embedded with different communication technologies such as Wi-Fi, Bluetooth, near field communication (NFC) [2]–[4]. Sensors may be inbuilt or externally interfaced to smart phones. Human carried sensors embedded mobile phones can be used for monitoring different environmental factors such as temperature, humidity, urban noise pollution, carbon footprint, air pollution, and urban traffic [2], [3].

Human mobility enables collection of mobile phone sensor data either by forming cooperative sensing task with surrounding neighbors, or individual user's mobile phone may simply send its sensor data to designated destinations such as central or cloud servers to do further processing and mapping of sensor data [2], [4], [6]. In both cases, sensing task assignment to participating mobile phone users and sending requested sensor data to designated destination can be done through *ad hoc* or infrastructure oriented networking [5], [7], [8].

In the former case (cooperative mobile phone sensing), formation of cooperative mobile phone sensing task requires regular lookup for neighbors, processing and exchange of messages, security, and trust protocols [6], [9]. Dynamic and unpredictable human mobility nature and activities affect the performance of cooperative mobile phone sensing task. The later type of mobile phone sensing activity (noncooperative sensing task) can be useful for sparsely populated and dynamically changing human networks, where availability of neighbors is sparse or changing in a short period. Our work is concerned with later case, i.e., mobile phone sensing at individual user level, which is also useful when heterogeneous sensing task assignment for each individual user is required.

Irrespective of scale of mobile phone sensing applications, for continuous and regular interval of sensing activity, optimization of energy consumption is an important issue. Under random waypoint (RWP) mobility model, there has been enough theoretical and practical work done on optimization of energy consumption and improving sensing area coverage for both static and mobile networks [10], [11].

Mobile phone sensing area coverage depends on sensing range and velocity of human mobility. Levy walk (LW) depicts statistical properties of human mobility patterns [12]–[16]. Rhee *et al.* [12], [13] describe the characteristics of human walk mobility and provides analytical description of LW mobility model. In [12] and [13], real human traces are used for analysis and report that independent of geographical constraints, the heavy-tail tendency of flight length distribution, super- and subdiffusive mean-square displacement features must be

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inherent in human walk mobility models. Birand *et al.* [14] explore dynamic graph properties under LW mobility model. In this, they explain that decrease of LW mobility parameter α leads to high-dynamic human networks [14] and on increase leads to low-dynamic human networks. Sheng *et al.* [6] and Hachem *et al.* [17] assume that users are aware of their path. In [6], they use knowledge of mobile phone users path for cloud based collaborative mobile phone sensing. In [17], users path information is used for reducing the number of participatory users.

Thejaswini *et al.* [1] propose a novel sampling algorithm based on human-walk velocity for mobile phone sensing and analyze how the velocity of human-walk affects the sensing area coverage and energy consumption at individual mobile phone user level. In this, performance is analyzed under existing LW mobility model by considering location trace of slow, medium, and fast moving LW nodes with an average velocity of 2.33, 2.26, and 2.04 m/s, respectively, with total mobility duration of 16 000 s [18]. The results show that mobile phone sensor sampling with respect to considered users walking velocity (1.0 m/s) reduces spatial overlap of sensing area and energy consumption of sensing process.

In real world, as mobile phones are carried by humans, their mobility characteristics and geographical constraints have an impact on mobile phone sensing applications. The velocity of humans will be varying according to their activities [19]–[21]. LW mobility model does not consider geographical features such as roads, buildings, and obstacles into account [12], [13]. Under real-world human traces, degree of spatial regularities is high and constrained by geographical features such as road width and length.

It is necessary to validate the performance analysis of mobile phone sensing algorithms by considering real-human mobility trace data. This paper provides significant improvement over the mobile phone sensor sampling algorithm proposed in [1], in particular by modifying the algorithm for handling real-world human traces and some of the corresponding mathematical models. The location traces are collected on daily basis using GPS-enabled mobile phones. To improve the sensing area coverage, percentage of allowed overlap of sensing area coverage is formulated mathematically. Mobile phone sensing activity requires energy efficient sensing task management methods. Sensing activity with GPS may drain significant amount of mobile phone battery power, affecting other applications running on it. Ensuring required spatial coverage with minimal energy consumption is an important issue under mobile phone sensing. Performance is analyzed and evaluated in terms of sensing area coverage and battery energy consumption by considering average velocity of respective location trace of individuals.

Compared to general regular sensor data sampling method, the proposed mobile phone sensor sampling with respect to mobile phone users average velocity performs better in terms of both spatial coverage and reduces battery energy consumption. This is achieved by suppressing unnecessary spatial overlaps caused by human mobility characteristics such as spatial regularities and pause duration (users are not moving).

This paper is organized as follows. Section II gives description of considered system models for proposed work. Section III discusses proposed sampling algorithm for mobile phone sensing. Section IV discusses evaluation of simulation results and Section V concludes the paper.

II. System Model

For simulation of proposed mobile phone sensor sampling algorithm, considered models, methodologies, and assumptions are described in this section.

A. Location Trace Data Collection from GPS-Enabled Mobile Phones

We have developed an android application for collecting location trace of persons using GPS-enabled mobile phones on daily basis [22]–[26]. As the proposed work is concerned with mobile phone sensing applications, it is assumed that for computing location, mobile phones use inbuilt GPS. The application logs a location record at every second, which consists of latitude, longitude, satellite time, and speed values. Android phone id or date and time of logged data is used to differentiate and identify individual mobile phone users [22], [27]. The logged data are uploaded to server at regular interval of time (30 s). The android application is distributed to 15 volunteers and their location traces obtained from end of April 2014 to May 2014 is considered for analysis of proposed work. Volunteers can run application whenever they are interested, except when they are moving in vehicles. The proposed work is relevant to mobile phone sensor sampling based on average velocity of human's and does not consider vehicular velocity. There is no restriction on them as not to use the application when they are working or sitting at one place, because pause duration of users is also an important parameter in analyzing the proposed work. There is no restriction on collection of location data at any particular geolocation and on duration. In this paper, the objective is not to classify exactly the human activities but to consider and analyze the effect of human mobility patterns and velocity on sensing area coverage and energy consumption for mobile phone sensing.

B. Processing GPS Data

The location trace of each individual mobile phone user may contain error due to very poor position accuracy from mobile phone GPS device [26]. There are many reasons for inaccuracy in GPS data such as receiver clock error, multipath effect, selective availability, ionospheric error, geometric dilution of precision error, nonline of sight between mobile phone GPS receiver and satellite, and low-battery power in mobile phones [28], [29]. For more information on GPS, error analysis and correction methods refer [28]–[30]. Due to errors in GPS data, location trace may have discontinuity in time. Rhee *et al.* [12] and Azevedo *et al.* [31] explain some of the methods to analyze and correct the collected raw location traces. In [31], differential correction is used to improve the GPS position accuracy and displacement is fixed to be $\leq$2.5 m/s. Rhee *et al.* [12] explain rectangular, angle, and pause-based methods to extract the flight from raw GPS traces. In [12], human walking speed is assumed to be 1 m/s to extract the pause time and discontinuity in traces. In this paper, GPS error data are removed by considering maximum distance traveled by normal person at every second to be less than $\text{velocity}_{\text{threshold}}$ meters, where $\text{velocity}_{\text{threshold}}$ gives threshold velocity value. For example, to consider only human walk traces, $\text{velocity}_{\text{threshold}}$ is set to 1.5 m/s [12], [13], [31]. On daily basis, if the time difference between two successive data logs is greater than 5 s, then it is assumed that there is discontinuity in the location trace. Consider successive data logs with time t_1 and t_2, let δt be the time difference, then $\delta t = t_2 - t_1$, where $t_2 > t_1$. If $\delta t > 5$ s, then it is assumed that there is discontinuity in location tracing and it is considered that t_2 is restart time of location trace again. Duration δt is not accountable for sensing process neither used for calculating pause time or traveled distance for mobile phone sensing activity. In other words, for discontinuity time periods, it is assumed that sensing application is stopped. On restart of location trace, we assume that sensing processes is restarted.

C. Projection of Location Trace

Mobile phone users are termed as mobile phones or mobile nodes. The filtered and processed location trace of each individual, which is collected on daily basis, has to be modified to fit as mobility trace input to proposed sampling algorithm. Let (γ, μ) be the latitude and longitude geopoints pair. Let φ be the colatitude, where $\varphi = 90^\circ - \gamma$ and *R* be the radius of earth. Spherical projection formulas are used (1) to project (γ, μ) geopoint pairs on two-dimensional (2-D) plane as (x, y) coordinate pair [26]. The projected individual persons location trace is considered as a mobile node location trace, for analyzing proposed sampling algorithm

$$\begin{aligned} x &= R * \sin\varphi * \cos\mu \\ y &= R * \sin\varphi * \sin\mu. \end{aligned} \tag{1}$$

D. Sensing and Energy Model

Furthermore, for simulating proposed algorithm, it is assumed that mobile nodes are embedded with required sensors and GPS for getting location coordinates.

Consider individual mobile node M. Let T be the total mobility duration of Mth node in an area A. Let n be the total number of sensors embedded to Mth mobile node. Let r_i be the sensing range of ith sensor, where $i = 1, 2, \ldots, n$. Disk model is considered for sensing range of each sensor (Fig. 1). Let t_i be the sampling interval of ith sensor. When mobile node moves in a straight line path with constant velocity v, without pause or change of direction, then t_i for nonoverlap sensing coverage with respect to ith sensor (Fig. 1) is given by

$$t_i = 2 * \frac{r_i}{v}. \tag{2}$$

Let v_{hm} be the average or preferred velocity of human mobility, then (2) is given by

$$t_i = 2 * \frac{r_i}{v_{\text{hw}}}. \tag{3}$$

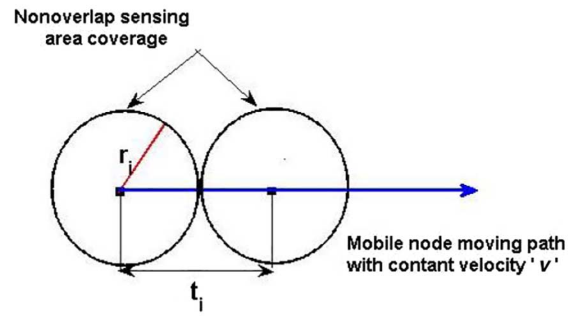

Fig. 1. Nonoverlap sensing area coverage.

ρ_i gives the total number of samples with respect to ith sensor over total mobility duration T

$$\rho_i = \frac{T}{t_i}. \tag{4}$$

From (4), nonoverlap sensing coverage Cov_i of ith sensor is given by

$$\text{Cov}_i = \rho_i * \pi * r_i^2. \tag{5}$$

It is assumed that mobile nodes have enough memory space to store sensed location points. Let ι be the total number of bytes required to store a sensor sample location record, which consist of location coordinates, speed, and time data. Total memory space required to store location records of any ith sensor data samples ρ_i is $\iota * \rho_i$. For example, if a sensor sample location record is of size 48 bytes, then to store 20 sensor samples location data, it requires 960 bytes of memory.

We consider same energy model used in [1]. Let energy consumed by Mth mobile node battery for sensing and processing a sample data of ith sensor ϵ_i, to be one unit and energy consumed for getting a sensed location sample (from GPS) ε_i also to be one unit. The total energy consumed for sensor (ϕ_i) and location samples (ψ_i) over T for Mth mobile node, ith sensor is given by (6) and (7), respectively. Equation (8) gives total energy consumed by ith sensor (E_i) and (9) gives total energy consumed by all the sensors (E_M) embedded to Mth mobile node for mobile phone sensing activity including sensed location sampling (from GPS)

$$\phi_i = \sum_{x=1}^{\rho_i} \epsilon_{ix} \tag{6}$$

$$\psi_i = \sum_{x=1}^{\rho_i} \varepsilon_{ix} \tag{7}$$

$$E_i = \phi_i + \psi_i \tag{8}$$

$$E_M = \sum_{i=1}^{n} E_i. \tag{9}$$

In particular, the effect of velocity of human mobility v_{hm} value on sensing area coverage (Cov_i) and energy consumption (E_M) for mobile phone sensing activity is analyzed by considering the proposed mobile phone sensor sampling method and general regular sensor sampling method.

III. Proposed Sampling Algorithm for Mobile Phone Sensing

Human walk characteristic consists of flight truncations and pause [12], [13]. Geographical constraints such as roadways, streets, city infrastructure (market places, buildings, trees, small shops), boundaries, human intensions, and contexts such as home coming, traveling to working places, and daily activities such as walking, jogging leads to spatial regularities, pause, and flight truncations in human mobility patterns [12], [13]. If (3) is followed, mobile phone users flight truncations, pause time, and spatial regularities leading to spatial overlaps when mobile phone-based sensing area coverage is considered. The human walk velocity-based mobile phone sensor sampling algorithm proposed in [1] is modified to fit the real-human location trace and pseudocode is given in Algorithm 1.

In Algorithm 1, v_{hm} value can be adaptive and changes according to individual persons mobility context. For analyzing the effect of velocity of human mobility on spatial coverage and energy consumption, each individual location trace is classified based on normal walking speed (velocity$_{\mathrm{threshold}} < 1.5$ m/s), and high velocity (velocity$_{\mathrm{threshold}} < 9.0$ m/s) [19]–[21], [32]. The average velocity calculated using the processed and filtered location trace is considered as v_{hm} value for respective projected location trace. In Algorithm 1, mobile phone sensors range r_i are grouped into unique subsets K where $K \leq n$, such that in each subset, sensor's range differ with respect to each other by $\leq G_r * r_{\max(i)}$, where G_r is the threshold range to group sensors and $r_{\max(i)}$ is the maximum sensor range of respective subset ([1], Algorithm 1, step 4). For example, if a mobile node consists of five sensors and their sensing ranges in meters are represented in order, say $B = \{10, 13, 15, 17, 20\}$ and assumed value of $G_r = \frac{3}{4}$ m. Then, out of many combinations set *B* can be grouped into unique subsets, {10, 13} and {15, 17, 20}. The number of sensed location samples is reduced by grouping sensors into K number of unique subsets and in each subset, only for the maximum sensor range $r_{\max(i)}$, location samples are considered with corresponding sensor samples.

Under LW mobility model, mobile nodes movement path is hardly straight and consists of flight truncations and pause [12], [13]. In LW mobility model, geographical constraints are not considered [12], [13]. Real-human mobility traces consist spatial regularity and pause duration, which are the main causes of sensing area overlap. In [1], the allowed degree of spatial overlap is fixed to $t_{\max(i)} * \frac{3}{4}$ m/s (Algorithm 1, step 22). It means that 25% of spatial overlap is allowed between any pair of sensor samples coverage area. The mobile phone users path is constrained by road or streets width. From most of observed individual persons location traces, users take same path or road with some meter differences (depends on road width).

This pattern increases the degree of spatial regularity. Number of sensor samples will be decreased with the decrement of allowed percentage of spatial overlap [33], [34]. Melissen and Schuur [33] deal mathematical formulas for covering a rectangle with circles. In mobile phone sensor sampling process, sensed location point is the center of circle. When mobile phone user walk in same path and if distance between any two sensed location points is $<2r_i$, overlap between sensing area will occur. If required spatial overlap is not allowed

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Algorithm 1. Pseudocode of sampling algorithm for mobile phone sensing

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1: Consider projected trace of any M^{th} mobile phone user as mobility trace input to M^{th} mobile node. Assume mobile node M is embedded with n number of sensors. Set v_{hm} value to be the average velocity of respective M^{th} node mobility trace. Let total mobility duration be T.
2: Let t_i be the sampling interval of i^{th} sensor, $i = 1, 2, .., n$, and $Gr = \frac{3}{4}$.
3: Let B be the set of sensing ranges r_i, $i = 1, 2, .., n$.
4: Group B into number of unique subsets, such that $C \subseteq B$ and let $r_{max(i)}$ and $r_{min(i)}$ be the maximum and minimum sensor range respectively and $\{r_i | r_i, r_{max(i)}, r_{min(i)} \in C, r_i \geq (Gr * r_{max(i)}) \wedge r_i \leq r_{max(i)}\}$. Let K represents total number of unique subsets of B, then $K \leq n$.
5: t_{start} is starting sample time $\forall i$ sensors.
6: $\forall K$ number of unique subsets, follow same sampling procedure given below
7: Calculate $dis_{thresold}$ value using equations (10) and (11) appropriately.
8: Let maximum sampling interval in any subset C be $t_{max(i)}$
9: d_i term is used for incrementing all sensors i sampling interval, where $i \in C$
10: Let τ be the timer, and $d_i = t_{start}$ and $t_{start} < T$
11: start timer τ
12: **while** $(\tau \leq T)$ **do**
13:     Start of initial sensor samples collection
14:     At $\tau = t_{start}$ get GPS current location coordinates
15:     Get sensor data of all sensors $i | i \in C$
16:     Store current location coordinates as previous location
17:     $d_i = d_i + t_i, \forall i$
18:     **if** $(d_i = \tau \wedge d_i < t_{max(i)})$ **then**
19:         Get all i sensors data where $t_i \neq t_{max(i)}$
20:         $d_i = d_i + t_i$ where $t_i \neq t_{max(i)}$
21:     **end if**
22:     End of initial sensor samples collection
23:     **for** $j \leftarrow t_{max(i)} : t_{max(i)}, T$ **do**
24:         **if** $j = \tau$ **then**
25:             Get GPS current location coordinates
26:             Find the minimum distance between all previous and current location.
27:             **if** (minimum distance $< dis_{threshold}$) **then**
28:                 Skip sensing process $\forall i$.
29:                 $\forall i, d_i = d_i + t_i * 2$
30:             **end if**
31:             **if** (minimum distance $> dis_{threshold}$) **then**
32:                 Get i^{th} sensor data and $t_i = t_{max(i)}$
33:                 **if** $(d_i = \tau \wedge d_i < j)$ **then**
34:                     Get all i sensors data where $t_i \neq t_{max(i)}$
35:                     $d_i = d_i + t_i$ where $t_i \neq t_{max(i)}$
36:                 **end if**
37:             **end if**
38:             Store current location coordinates as previous location
39:         **end if**
40:     **end for**
41: **end while**

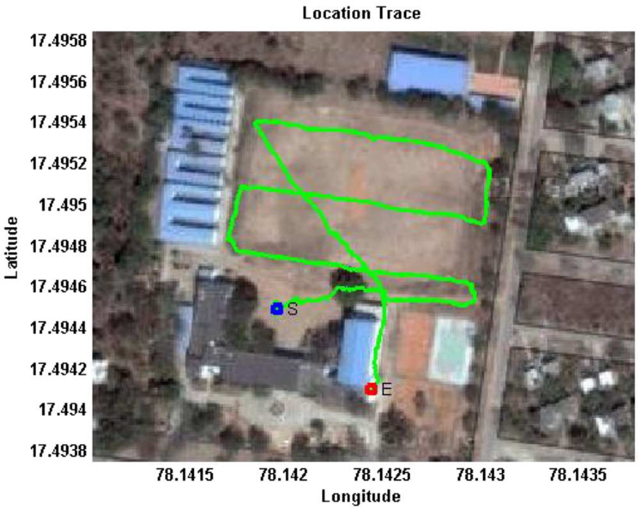

Fig. 2. Sensing area coverage and spatial regularity: location trace on map.

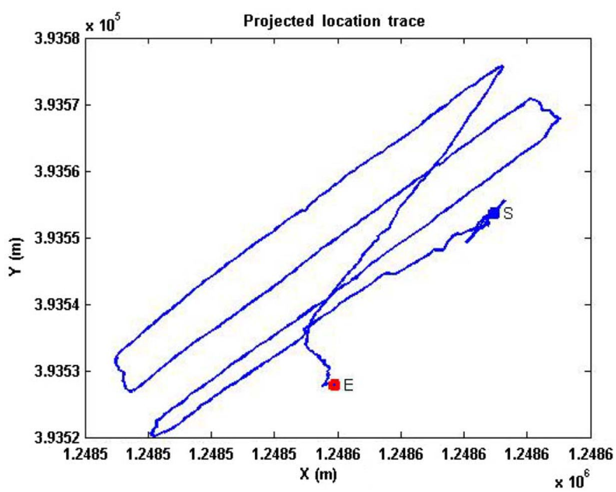

Fig. 3. Sensing area coverage and spatial regularity: projected location trace.

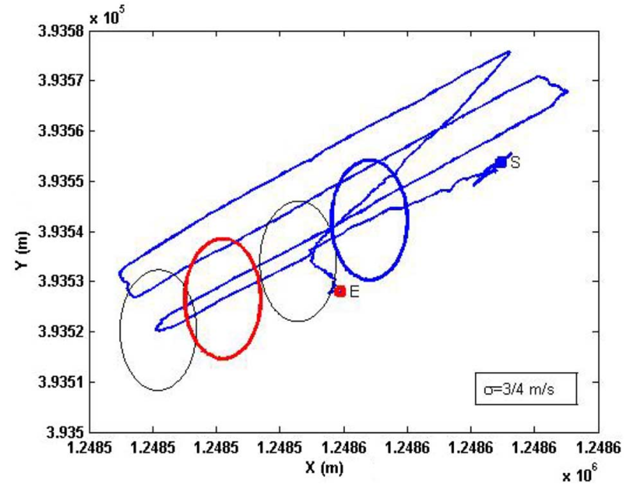

Fig. 4. Sensing area coverage and spatial regularity: general sampling method for mobile phone sensing.

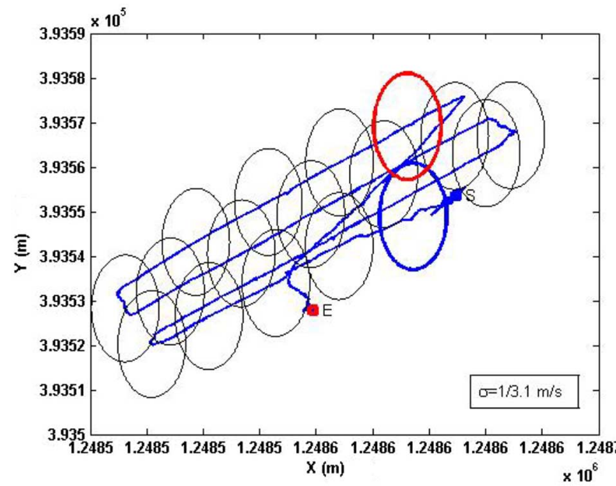

Fig. 5. Sensing area coverage and spatial regularity: proposed sampling method for mobile phone sensing.

between sensing range, total coverage area of mobile phone sensor will be reduced.

To show the effect of spatial regularity of human mobility on mobile phone sensing coverage, consider Fig. 2 which shows location trace of a individual mobile phone user on map [25], [35]. Fig. 3 represents the projected location trace of Fig. 2. Fig. 4 shows the result plot after applying mobile phone sensor sampling algorithm on projected location trace without any modification ([1], Algorithm 1), i.e., in between sensor data samples, allowed spatial overlap (sensing coverage area) is 25%. Average velocity $v_{\mathrm{hm}} = 1.1$ m/s (calculated from respective user location trace, Fig. 2) and assumed $r_i = 12$ m. Fig. 4 shows very less coverage (only 4 circles which represent sensing area coverage). For considered location trace, allowing 25% spatial overlap between any pair of $i\mathrm{th}$ sensor samples reduces sensing coverage.

To overcome the problem, which is described above, to an extent, overlapping between sensing area has to be allowed. In this paper, a new variable is introduced called as σ in m/s (10) to improve the sensing coverage area. For each K number of unique subset of sensor ranges (Algorithm 1), σ gives allowed percentage of overlap between sensing area. σ value is calculated as given in (10) and its value depends on χ, which stands for road width, minimum and maximum sensor range $r_{\min(i)}$ and $r_{\max(i)}$ (m) of considered unique sensor range subset. $(1-\sigma) * 100$ gives allowed spatial overlap area in percentage. It is assumed that in real sense χ value can be manually assigned by users or estimated based on geolocation information [25], [35]. Fig. 5 shows the result plot after applying modified mobile phone sensor sampling algorithm (Algorithm 1) on projected location trace (Fig. 2). Fig. 5 shows improved area coverage as 68% ($\sigma = \frac{1}{3.1}$ m/s, $\chi = 29$ m, and $r_i = 12$ m) spatial overlap is allowed

$$\sigma = \begin{cases} 0.25, & \text{if } \chi < r_{\min(i)} \\ \frac{\chi * 10}{r_{\max(i)}}, & \text{if } \chi > r_{\min(i)} \\ \frac{\chi * 7.5}{r_{\max(i)}}, & \text{if } \chi > r_{\min(i)} \wedge r_{\max(i)} \leq 15\,\mathrm{m} \\ \frac{\chi * 4.7}{r_{\max(i)}}, & \text{if } \chi > r_{\min(i)} \wedge r_{\max(i)} \geq 20\,\mathrm{m}. \end{cases} \tag{10}$$

By calculating the distance between previous and current locations, we reduce the spatial overlap caused by individual

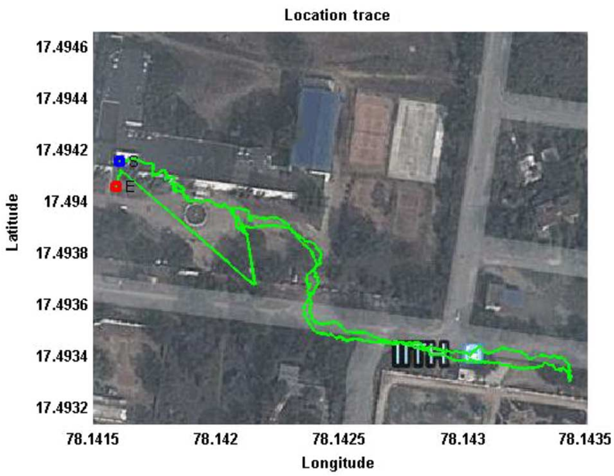

Fig. 6. Reduction of spatial overlap: location trace on Google map.

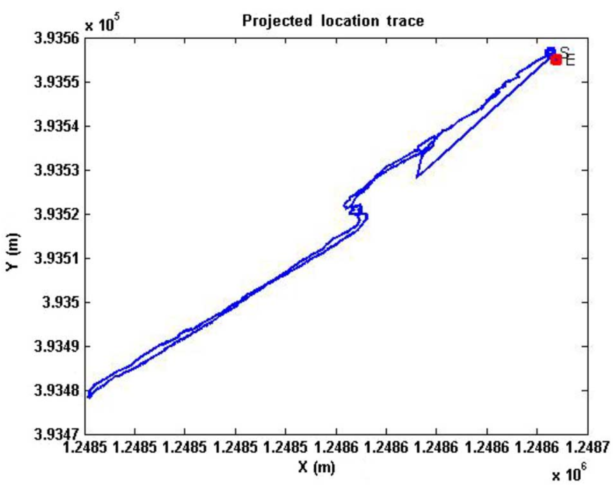

Fig. 7. Reduction of spatial overlap: projected location trace.

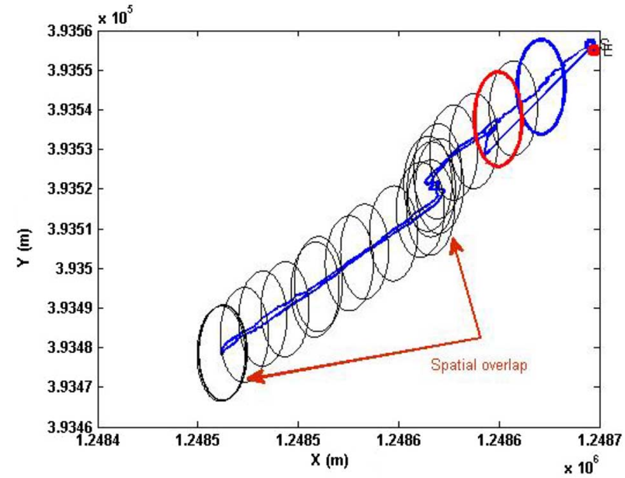

Fig. 8. Reduction of spatial overlap: general sampling method for mobile phone sensing.

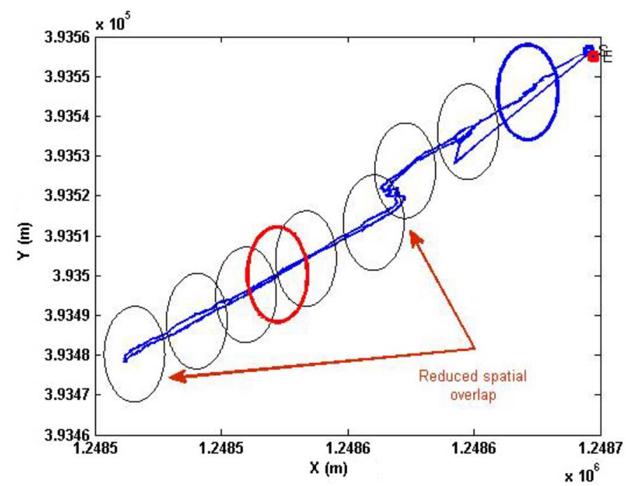

Fig. 9. Reduction of spatial overlap: proposed sampling method for mobile phone sensing.

mobile phone users spatial regularity, pause, and flight truncations. $\mathrm{dis}_{\mathrm{threshold}}$ is used to represent threshold distance value, which has to be covered by a mobile node, between successive sampling intervals t_i time. If minimum distance calculated between all previous sensed location samples and current location sample is less than $\mathrm{dis}_{\mathrm{threshold}}$ (11), then current sensing process is skipped for all the sensors of that particular subset. If total number of unique subsets $K < n$, then total energy consumed by any Mth mobile node will be reduced. Equations (8) and (9) are changed to (12), as in each subset only for maximum range sensor, sensed location samples are considered, therefore $i = 1, 2, \ldots, K$ for location samples ψ_i

$$\mathrm{dis}_{\mathrm{threshold}} = t_{\max(i)} * \sigma \tag{11}$$

$$E = \sum_{i=1}^{n} \phi_i + \sum_{i=1}^{K} \psi_i. \tag{12}$$

Consider Fig. 6 which shows the location trace of an individual mobile phone user and Fig. 7 represents its projected location trace. Consider only walking activity ($\mathrm{velocity}_{\mathrm{thresod}} \leq 1.5$ m/s). Average velocity v_{hm} of projected location trace is 0.92 m/s, assumed range of sensor $r_i = 12$ m. Figs. 8 and 9 show result plot of general regular sampling method and proposed sampling method on considered projected location trace, respectively. In general regular sampling method, sensing is done at regular interval of time according to (3), and also respective sensed location data are collected (from GPS). In Figs. 8 and 9, circles represent sensing range. Overlaps of circles in Fig. 8 represent spatial overlap of sensing area due to either flight truncation, pause, or spatial regularities. Fig. 9 shows reduction in number of spatial overlap of sensing area for the same trace after applying proposed sampling algorithm (Algorithm 1).

IV. Simulation Results and Discussion

In this section, proposed sampling algorithm is analyzed for mobile phone sensing in terms of average battery energy consumed and spatial coverage using real human mobility trace. In real sense, the sensing area covered results can be considered as earth surface area covered by mobile phone sensors. The term general regular sampling (GRS) represents general sampling method, i.e., sensor data sampling with regular interval of time

TABLE I
SIMULATION PARAMETERS

No. of sensors	Range (m)	χ (m)	σ
Single sensor	12	29	0.32
Multisensors Sensor1, Sensor2, Sensor3	20,17,15	29	0.19

t_i (3). The term velocity of human mobility-based sampling (VHMS) represents proposed sampling method. For analyzing the impact of human velocity on mobile phone sensing, location trace of mobile phone users is classified into two categories. One is normal human walking, where $\mathrm{velocity}_{\mathrm{threshold}}$ value is set to $\leq$1.5 m/s and another is high velocity of human mobility for which $\mathrm{velocity}_{\mathrm{threshold}}$ value is set to $<$9.0 m/s. Specifically, locations traces of persons where activities such as jogging and running involved are considered for obtaining high velocity of human mobility.

By substituting the values of v_{hm}, T (obtained from Mth mobile phone user projected trace) and assumed sensor range r_i in (2)–(4) gives nonoverlap spatial coverage Cov_i(5) and total energy consumption E_M (9). Cov_i will be considered as required ith sensor coverage area and E_M as energy consumption limit to be achieved by considered sampling methods. Let $\mathrm{VHMS}_{\mathrm{Cov}i}$ and $\mathrm{VHMS}_{\mathrm{EM}}$ be the sensing coverage area and total energy consumption achieved with VHMS sampling method. Let $\mathrm{GRS}_{\mathrm{Cov}i}$ and $\mathrm{GRS}_{\mathrm{EM}}$ be the sensing coverage area and total energy consumption achieved with GRS sampling method.

The importance of the proposed work is to achieve maximum possible spatial coverage with less energy consumption. For any considered sampling method, if energy consumption of mobile nodes is less than or equal to respective E_M value (13) and (14), then the method is considered as suitable, otherwise it is considered as unsuitable even though it has achieved respective sensor coverage area greater than respective Cov_i value

$$\mathrm{VHMS}_{\mathrm{EM}} \leq E_M \quad (13)$$
$$\mathrm{GRS}_{\mathrm{EM}} \leq E_M. \quad (14)$$

A. Single Sensor Results

First, only normal human walking activity is considered, where average velocity v_{hm} is $\leq$1.5 m/s. It is assumed that mobile nodes are embedded with only single sensor ($i = 1$) and for all mobile nodes, sensor range r_i is set to 12 m (Table I). For all the location traces, we set $\chi = 29$ m (Table I). χ value may vary from one geographical area to another. The results are plotted with respect to each classified individual users projected location trace (users are indexed, i.e., $M = 1, 2, \ldots, 10$). Table II shows the location trace details of each indexed individual, where considered $\mathrm{velocity}_{\mathrm{threshold}}$ value is $\leq$1.5 m/s.

Figs. 10 and 11 show sensing area covered and energy consumed for VHMS and GRS methods. In Fig. 10, GRS method has high-sensing coverage for all the considered mobile phone users, but consumes more energy than respective E_M. Fig. 11 shows that, for proposed VHMS method, energy consumption is reduced for all indexed users compared to GRS method.

TABLE II
MOBILE PHONE USERS LOCATION TRACE DATA FOR SINGLE AND MULTISENSORS ($\mathrm{velocity}_{\mathrm{threshold}}$ $\leq$1.5 M/S)

Idx.	Avg. dis. (m/s)	Tol. dis (m)	Min. velo. (m/s)	Max. velo. (m/s)	v_{hm} avg. velo. (m/s)	T tol. dur. (s)	Tol. pause dur. (s)
1	1.1176	2.16E+03	0.25	1.5	1.1302	1932	306
2	0.4811	4.76E+02	0.25	1.5	0.897	989	628
3	0.3662	858.364	0.25	1.5	1.0495	2341	1750
4	0.1141	77.4559	0.25	1.5	0.9518	678	618
5	1.3066	1.41E+03	0.25	1.5	1.169	1078	84
6	1.1854	1.33E+03	0.36	1.5	1.1588	1121	121
7	0.4037	641.9567	0.25	1.5	1.0395	1589	1073
8	1.0662	1.76E+03	0.25	1.5	1.026	1649	1520
9	0.4738	2.91E+03	0.25	1.5	1.0633	6147	313
10	0.5289	1.23E+03	0.25	1.5	1.3208	2323	4055

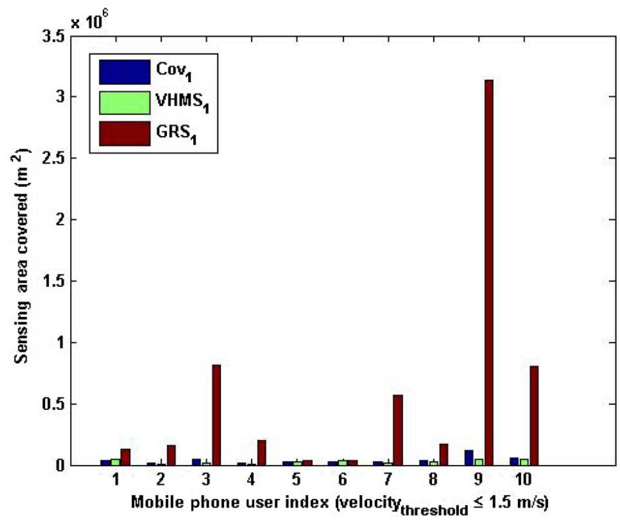

Fig. 10. Sensing area covered.

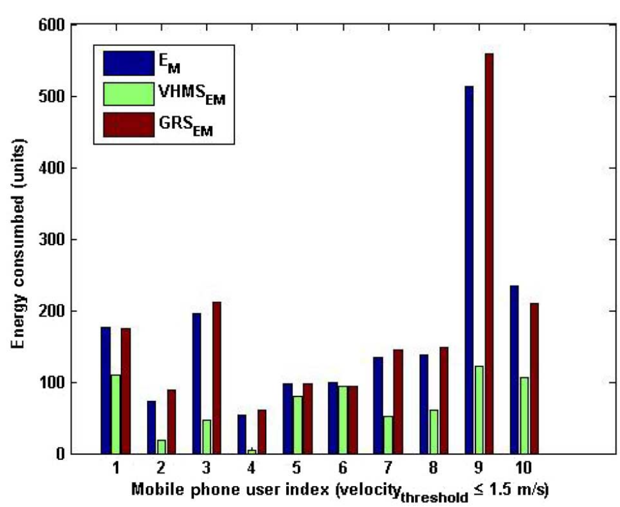

Fig. 11. Energy consumed.

VHMS method reduces spatial overlaps by reducing number of sampling process. Better performance is required in terms of both spatial coverage and reduction of energy consumption. Because of over consumption of energy and high level of spatial overlap, GRS method is not suitable sensor sampling method

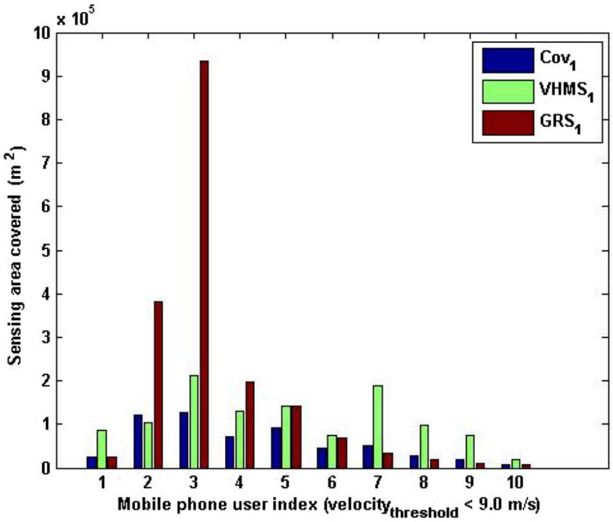

Fig. 12. Sensing area covered.

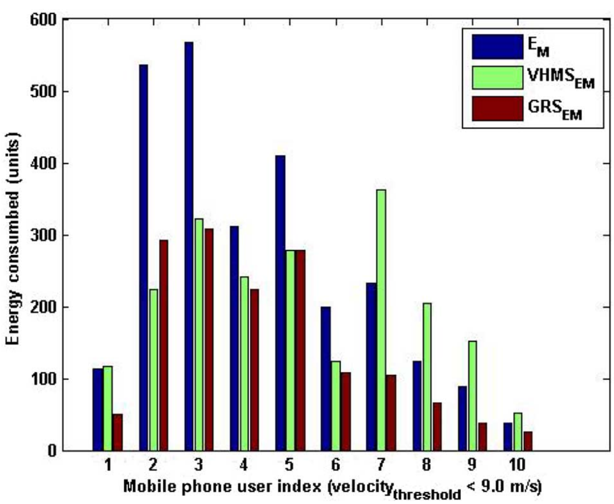

Fig. 13. Energy consumed.

under normal human walking. Combining the results of Figs. 10 and 11, when users are walking with normal speed i.e., average v_{hm} $\leq$1.5 m/s, proposed algorithm suits well, covers possible sensing area with less energy consumption for mobile phone sensing activity.

Figs. 12 and 13 show the results of sensing area coverage and energy consumptions when $\mathrm{velocity}_{\mathrm{threshold}}$ is set to <9.0 m/s. Table III shows the location trace details of each indexed individual, where considered $\mathrm{velocity}_{\mathrm{threshold}}$ value is <9.0 m/s, to consider high velocity of human mobility into account. Obtained v_{hm} values vary from 1.5 to 2.59 m/s (Table III). GRS consumes less energy than respective E_M and has good coverage compared to VHMS. Proposed method shows less coverage (Fig. 12) or it shows energy consumption greater than GRS (Fig. 13). Results of Figs. 12 and 13 show that GRS method is better choice, as it shows good spatial coverage and consumes energy within the limit of respective E_M. But on daily basis, jogging or running activity is of limited duration compared to

TABLE III
MOBILE PHONE USERS LOCATION TRACE DATA FOR SINGLE AND MULTISENSORS ($\mathrm{velocity}_{\mathrm{threshold}} < 9.0$ M/S)

Idx.	Avg. dis. (m/s)	Tol. dis (m)	Min. velo. (m/s)	Max. velo. (m/s)	v_{hm} avg. velo. (m/s)	T tol. dur. (s)	Tol. pause dur. (s)
1	2.7255	1.55E+03	0.25	5.02	2.7776	569	42
2	1.5426	4.96E+03	0.25	6.08	2.2985	3212	1406
3	1.3173	4.49E+03	0.25	5.25	2.0982	3407	1520
4	1.5149	3.77E+03	0.25	2.5	1.5033	2485	313
5	1.6612	5.43E+03	0.25	5.52	1.5137	3268	343
6	2.2331	2.68E+03	0.25	4.5	2.241	1198	195
7	2.5587	2.96E+03	0.25	7	2.5206	1151	124
8	2.6962	2.00E+03	0.25	4.25	2.3696	741	47
9	3.4787	1.53E+03	0.25	5	2.5973	434	73
10	1.6839	505.1615	0.31	2.57	1.5375	299	8

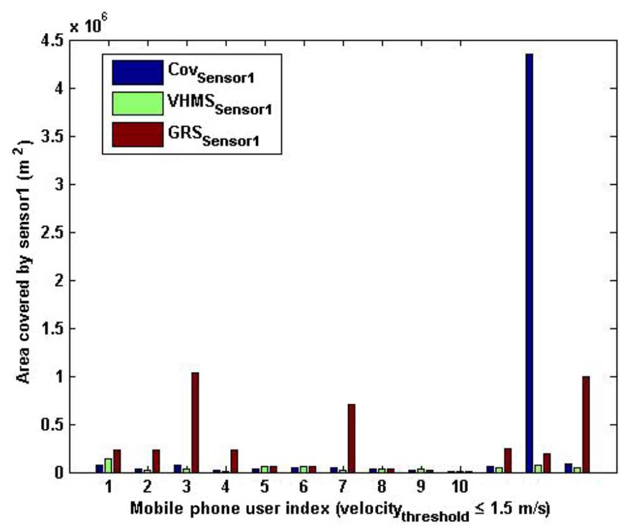

Fig. 14. Sensing area covered by Sensor1.

people walking with normal speed (<1.5 m/s). So, more preference will be given to the results when normal walking speed is considered.

B. Multi Sensor Results

Figs. 14–21 show performance analysis in terms of sensing area covered and energy consumed for mobile phone sensing activity with the assumption that each mobile node has 3 sensors. Considered 3 sensors are termed by Sensor1, Sensor2 and Sensor3 ($i = \mathrm{Sensor1}, \mathrm{Sensor2}, \mathrm{Sensor3}$), their sensing ranges are 20, 17, and 15 m, respectively. For Figs. 14–17 $\mathrm{velocity}_{\mathrm{threshold}}$ is $\leq$1.5 m/s. Figs. 14–16 show sensing area coverage for considered sensors. In Fig. 17, most of the cases, for all the sensors results, GRS crosses respective E_M limit. In GRS method, it is considered that for each sensor sampling process, mobile phone GPS is used to get current location record. In VHMS method, it is considered that GPS is used only for the maximum range sensor sampling in each subset of sensors.

For Figs. 18–21, $\mathrm{velocity}_{\mathrm{threshold}}$ is set <9.0 m/s. When velocity of human mobility is quite high, i.e., $v_{\mathrm{hm}} > 1.5$ m/s proposed VHMS does not achieve good spatial coverage compared to GRS method. The other choice will be to use GRS

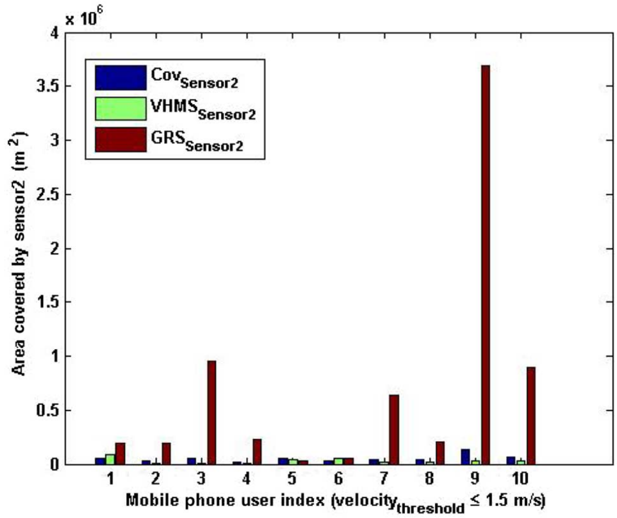

Fig. 15. Sensing area covered by Sensor2.

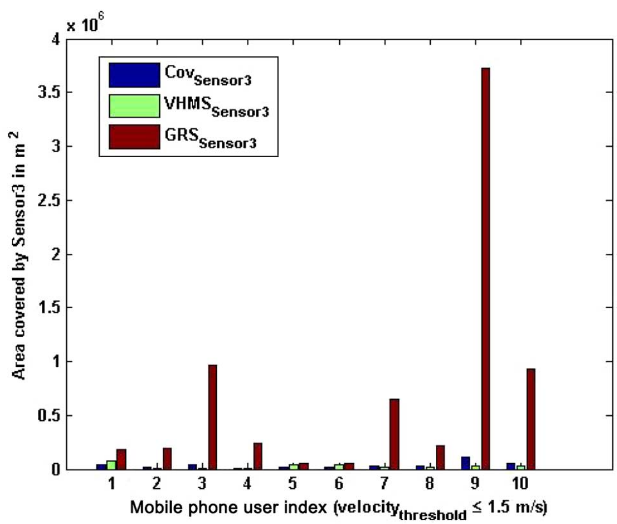

Fig. 16. Sensing area covered by Sensor3.

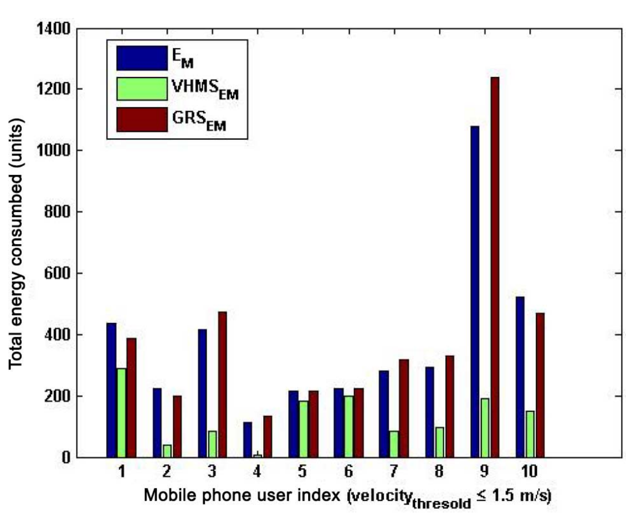

Fig. 17. Total energy consumed by all sensors.

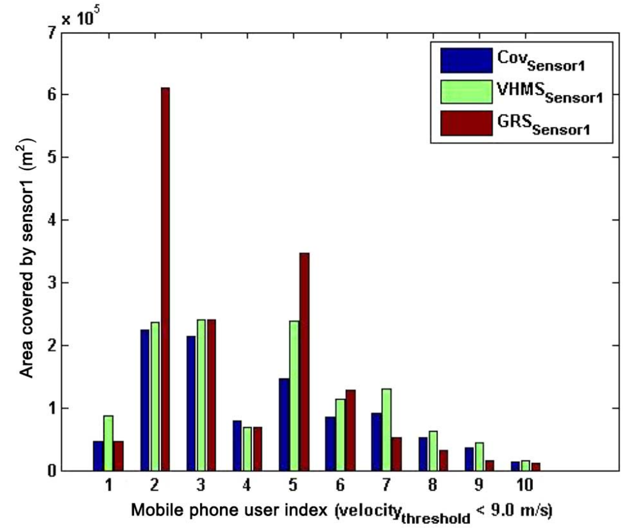

Fig. 18. Sensing area covered by Sensor1.

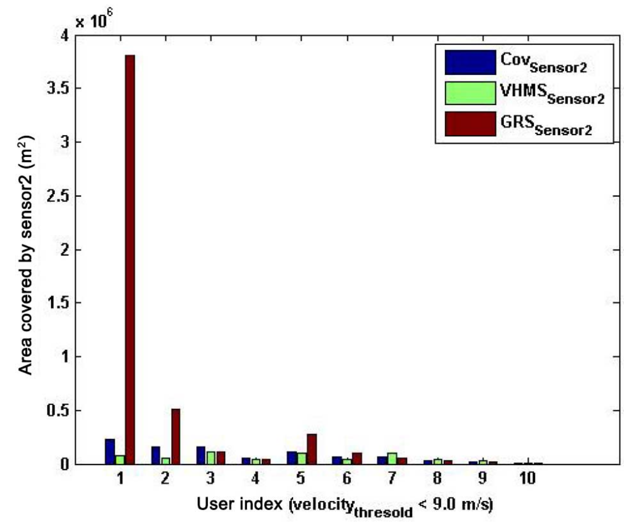

Fig. 19. Sensing area covered by Sensor2.

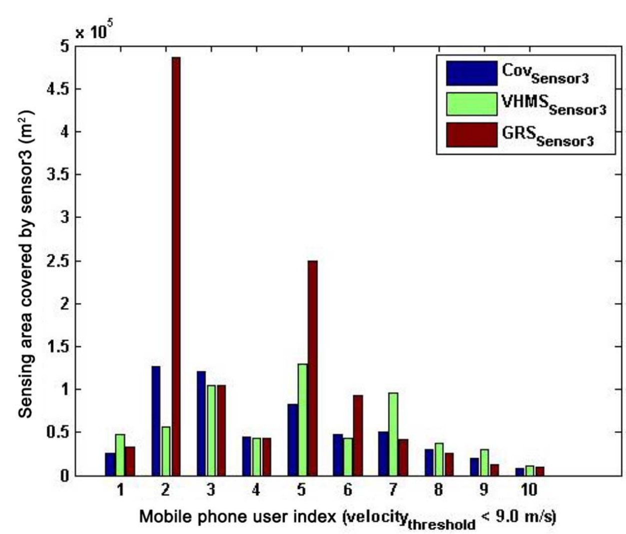

Fig. 20. Sensing area covered by Sensor3.

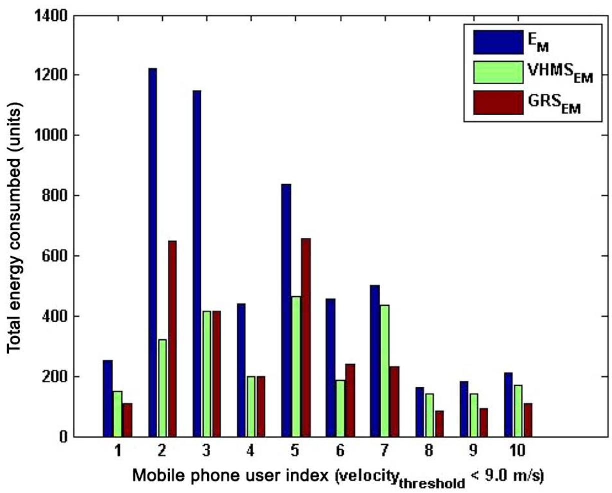

Fig. 21. Total energy consumed by all sensors.

method, as it consumes energy less than E_M and also achieves required spatial coverage. The results of VHMS and GRS under multisensor sampling activity depict the same conclusion of single sensor sampling activity that under normal walking speed, in terms of both reduction of energy consumption and sensing area coverage, proposed VHMS method gives better performance. When velocity of human mobility is high enough, GRS method will be the good choice.

V. Conclusion

Human mobility characteristics such as flight truncations, duration of pause, and spatial regularities cause spatial overlap for mobile phone-based or human centric sensing activity. Velocity of human mobility and geographical constraints affect mobile phone sensing coverage and battery energy consumption. Mobile phone sensor sampling chosen according to walking speed of individual and allowing spatial overlap to an extent, gives better performance in terms of both spatial coverage and reduction of battery energy consumption. For normal walking speed of human, the proposed mobile phone sensor sampling algorithm gives better performance in terms of both battery energy reduction and required area coverage by suppressing spatial overlaps caused by spatial regularities and pause duration. In future, an explicit performance analysis, which involves switching between proposed and general sampling method need to be considered when both normal and high velocity of human mobility happens interchangeably. Our future work also involves analyzing the effect of vehicular mobility (human in vehicles) on mobile phone sensing and developing an cooperative and more dynamic sensor sampling algorithm for mobile phone sensing activity.

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