Mobile Sensing in Metropolitan Area: Case Study in Beijing

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ABSTRACT
During the vast trend of urbanization, mobile sensing in metropolitan area has become an emerging fashion and prevailing technology to monitor the environmental changes and human activities in the city scale. In this paper, we propose a novel framework, namely, the Context-Aware Metropolitan Sensing (CAMS), to rise to the increasing challenges in context acquisition, context fidelity, context dynamics and context complexity. CAMS is an high level framework that focus on knowledge discovery among distributed or mobile users, and loose coupled with specific communication and networking technology. By a case study of Beijing road roughness evaluation, we propose decision-tree based machine learning algorithm to gain knowledge from 3-axis accelerometers and GPS receivers. The results show how the CAMS framework can be used to develop city-scale mobile sensing applications.

Author Keywords
Mobile sensing, context awareness, road roughness detection, machine learning, decision tree.

ACM Classification Keywords
H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms
Algorithms, Design, Human Factors, Measurement, Performance.

1. INTRODUCTION
In the past few years, a new trend of urban or metropolitan sensing and people-centric sensor network has become a major driving force of ubiquitous computing and context-aware applications. There have been many interesting applications utilizing context, many of them belong to Location Based Services (LBS).

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Sensor networks have been considered as a major enabling technology for realizing interactions between human perception and the physical world. We have seen oceans of demo systems and applications, which revealed people's ingenuity and great advancements in many aspects of sensor network technologies. Cuff concluded that 'embedded networked sensing had successfully shifted from the lab to the environment, and there would be an unprecedented move to the metropolitan area, where citizens will be the source of data collection' [1].

Towards a better understanding of the urban life, many research groups have been engaged in fine-grained monitoring of environment and people's activities. Center for Embedded Networked Sensing at UCLA[2] focuses on participatory urban sensing which emphasizes the involvement of individuals and community in the process of data collection and storage(e.g. PEIR[3]). MetroSense project of Dartmouth College presents a series of prototypes(e.g. BikeNet[4], CenceMe[5]) for people-centric data gathering, mainly by mobile phones.

Metropolitan sensing utilizes heterogeneous and distributed sensors to gain data about temperature, moisture, noise and air pollution. Spatial-temporal information which can be obtained from the GPS receiver is aligned to these environmental information for augmented perception and personal affair scheduling. However, great challenges still remain when we try to discover knowledge from data in metropolitan sensing systems. Henrichsen et al.[6] and Poslad[7] conclude the challenges in general applications respectively. In common, they use the concept context as 'any information that can be used to characterize the situation of an entity that is considered relevant to the interaction between a user and an application'[8]. Context-aware system is basically considered as system that can be aware of, and adapt to its situation in its physical, technical, and personal environments. Considering the specific requirements of metropolitan sensing, we highlight the following four challenges that need to be considered.

• **Context Acquisition**: In metropolitan sensing, sources of the information are embedded in the city-scale geometrical areas. The technical challenges for the infrastructure is how to accomplish demanding data collection and transmission tasks with extremely limited communication and computation power in sensor networks.

• **Context Fidelity**: In a citywide distributed sensor system, data may be incorrectly, incompletely, imprecisely defined, determined or predicted. Moreover, delay is incurred in exchanging dynamic context information and intermittent connectivity can even cause part of the information unknown.

• **Context Dynamics**: Most of the information in metropolitan sensing applications may exhibit a range of spatial-temporal characteristics. They are highly temporal dynamical. And data collectors (e.g. vehicles, people) are usually mobile or may vary across regions. Therefore, the dynamics render difficulties in obtaining an accurate set of the context information.

• **Context Complexity**: Information in metropolitan area may be distributed and partitioned, composed of multiple parts that are highly correlated. But the relationships may be implicit. They may be related by derivative rules that make a context dependent on another.

In this paper, we propose a primary framework for Context-Aware Metropolitan Sensing (CAMS), from context acquisition techniques to context utilization. The paper is organized as follows. In section 2, we describe our prototype and deployment of a taxicab-based metropolitan network that perform mobile sensing in Beijing. In section 3 we describe in detail the framework of CAMS and its components. In section 4 we show a case study of CAMS in road roughness evaluation of Beijing. Section 5 concludes the paper.

2. METROPOLITAN SENSING DEPLOYMENT

To build a context-aware metropolitan sensing system, the first question is how to collect and aggregate data in city scale. Definitely this is a huge challenge when we want to achieve this goal at relatively low cost and not so much labor-intensive deployment. Since 2009, we focus on building flexible and low-cost sensing infrastructure based on public transportation systems (especially taxicabs) to perform distributed sensing and operating tasks in an autonomous manner.

Figure 1. Beijing roads redrawn by ten taxicabs' traces

Figure 2. The city map of Beijing

The favorable feature of taxi-based metropolitan sensor network is that it can provide affordable and high density sensor coverage for the urban area. We analyze the GPS traces of over 28,000 taxis of Beijing , and find the mobility of taxi reveals great potential of metropolitan sensing: taxis can go anywhere at any time and perform sensing and operating task independent from people's manipulation. What is more impressing is that with a large time granularity, we can reconstruct the physical field of a city by a quite small proportion of vehicles. Fig. 1 shows the accumulative traces derived from 10 taxis in one day, and we can recognize the portrait of the city road network when contrast with a real city map (Fig. 2). We develop a prototype(Fig. 3) and deploy it on a group of 20 taxicabs and tour buses; each includes GPS receiver, temperature/humidity sensor, carbon-monoxide(CO) sensor and 3-axis accelerometer.

Figure 3. Mobile Devices for Metropolitan Sensing

3. CAMS FRAMEWORK

We propose a comprehensive framework for Context-Aware Metropolitan Sensing (CAMS). This framework is distinct from others, e.g. the framework proposed by Baldauf et al.[9], because it emphasizes on context sharing within the context community. Here we define a context community as a social network or community of users where they can exchange context in common interest. In metropolitan scenario, the capabilities of each user are quite constrained by the low power devices and the inherent limits of temporal and spatial surveillance range. Participatory context sharing will greatly enhance each individual's priori knowledge and situation awareness. Fig. 4 illustrates the overall aspects of CAMS framework. The framework can be divided into three stages.

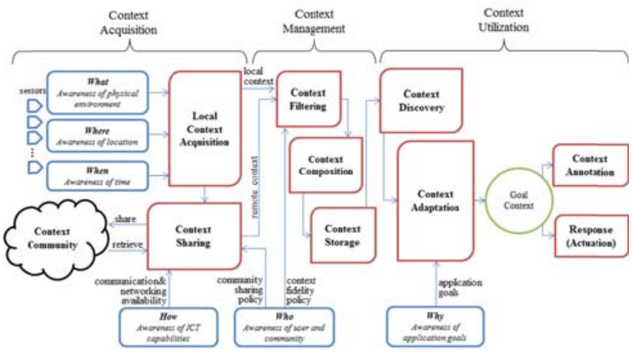

Figure 4. CAMS Framework

• **STAGE I: Context Acquisition**

Context acquisition acts as an enabling technology of the whole system, which includes local context acquisition and context sharing mechanism.

- Local context acquisition: acquire data from sensors which are embedded in the portable devices or professional equipment. This process may entail many sub-processes such as sensor calibration and sensor configuration (e.g. to set the sample rate or trigger threshold of events).
- Context sharing: in metropolitan sensing applications, the context of each user is quite limited in both temporal and spatial range. To achieve a global view of the urban area, users have to share information with others. Participatory context sharing will greatly enhance each individual's priori knowledge and situation awareness. Basically, context sharing mechanism is constrained by network availability (either infrastructure-based, such as GPRS/3G, or short-range wireless communication technologies, such as Zigbee, WiFi, etc.) and community sharing policy(the social network).

• **STAGE II: Context management**

Context management includes sub-stages of filtering, composition and storage.

- Context Filtering: data may be incorrectly, incompletely, imprecisely defined, determined or predicted. Filters only consider events within a certain range that adhere to context fidelity polices, which define the temporal granularity (duration and/or interval) and spatial granularity (absolute location or relative location) and accuracy. A major task of context filters is to deal with inconsistency in raw context from both local and remote users.
- Context Composition: multiple contexts are always linked and interrelated. Context composition will play a key role in converting low-level contexts (such as location, time and identities) into higher-level contexts (such as where and when a party is held). Combining several individual contextual values may generate a more precise understanding of the current situation than taking into account any individual context.
- Context Storage: includes both historical contexts and remote contexts, and these contexts are organized to support fast query-based retrieval. Life-cycle of context is important to maintain useful context and eliminate out-of-date ones.

• **STAGE III: Context Utilization**

Context utilization focuses on context discovery and adaptation.

- Context Discovery: reveals the application goal and efforts to search and retrieve related current contexts to perform further processing. Discovery of context may require search algorithms to locate particular matches in a very large context dataset. Context matching may also need to use complex (sematic) metadata models that are able to undertake matches in heterogeneous context spaces.
- Context Adaptation: performs the task of transition from the current context to the goal context. We may be satisfied when we see so many contexts about urban life created and retrieved, but it is really the relation of the current context to a goal context that is the essence of context-awareness. Machine learning algorithms will play key role in the knowledge discovery process.

4. CASE STUDY: ROAD ROUGHNESS EVALUATION IN BEIJING

4.1 Overview of Road Roughness Evaluation Techniques

Road roughness is a broad term that incorporates everything from potholes and cracks to the random deviations that exist in a profile. Detection of the road condition is important for safety and economic savings. To build a roughness index, existing methods of gauging the roughness are based either on visual inspections or using instrumented vehicles that take professional measurements. Nowadays, many smart phones, such as iPhone, are equipped with accelerometers and gyroscopes, and there are also built-in accelerometers in cars to improve suspension performance and increase ride comfort.

González[10] proposes a method using acceleration measurements and Fourier analysis to calculate the Power Spectral Density (PSD) function of the surface. According to ISO 8608, It classifies the profile into 'A' (very good), 'B' (good), 'C' (average), 'D' (poor) and 'E' (very poor) roughness indices. Liu et al.[11] presents an application procedure based on wavelet theory to offer supplementary information to a roughness index and provide additional information on the characteristics of the roughness profile of interests. Khoudeir et al.[12] suggests a method to characterize micro-roughness of road surfaces through image analysis.

However, most of the methods using acceleration measurements cannot deal with the dynamic change of urban road profile. Real-time and distributed data are desirable to generate a global view of city roads status. Utilizing CAMS framework, we propose a new road roughness evaluation method, based on participatory urban sensing.

4.2 Experiment Setup

To monitor and annotate road roughness conditions, we adopt the following types of sensors in our experiment:

- Accelerometers: collect the acceleration in three dimensions, while X-axis value reveals the accelerating or braking status, Y-axis value reveals the turn-left or turn-right actions, Z-axis reveals the vertical vibrations. In our experiments, we adopt a commercial device with max sample rate at 200Hz, accuracy at $10^{-3}g$ (g is gravitational acceleration).

- GPS receivers: commercial GPS module is used to obtain the absolute location, satellite time and instant speed.
- PC cameras: a big challenge in machine-learning of road roughness is the lacking of ground truth, i.e. how to examine a pothole derived from data analysis is really existed. We take human-in-the-loop judgments. PC camera is used to record the video of roads forward for off-line comparison. By synchronizing the video and the acceleration sensors, we could match the acceleration data with the road surface it represents.

4.3 Primary Results

Fig.5 is a sample waveform of the acceleration information when the car crossed a speed bump. We can see clearly from the figure that there is an obvious up-and-down in the Z-axis, with jitters in X- and Y- axis. Thus, the fluctuation in peak-peak value will be helpful index to identify the road surface condition.

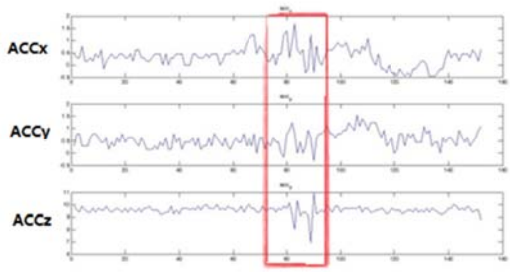

Figure 5. Sample Acceleration Waveform

Figure 6. Detected Road Surface Anomaly

4.4 Decision tree based machine learning method

To achieve Boolean classification for the normal and abnormal conditions in road surface detection, decision tree based method is a reasonable choice, especially when the construction of decision tree does not require any domain knowledge or parameter settings. Algorithms like ID3, C4.5 and CART adopt non-backtracking approach in which decision trees are constructed in a top-down recursive divide and conquer manner. In our case, at least four attributes should be considered: *x-acc*, *y-acc*, *z-acc* and *speed*. From the training dataset, we could derive correlations between the variables and road condition index (good or poor).

The algorithm to generate decision tree can be described as follows[13]:

Input:

- *D*: training dataset;
- *Attribute_list*: *x-acc*, *y-acc*, *z-acc* and *speed*
- *Attribute_seclection_criterion*: a procedure to determine the 'best' decision attribute

Output:

- The decision tree for road roughness evaluation

Methods:

(1) $A \leftarrow$ *Attribute_seclection_criterion*(*D*, *Attribute_list*)
(2) Assign *A* as decision attribute for node
(3) For each value of *A*, create new descendant of node
(4) Sort training examples to leaf node
(5) IF training examples perfectly classified, THEN STOP, ELSE iterate over new leaf nodes.

Here the procedure *Attribute_seclection_criterion* is critical for algorithm performance. We adopt information gain[14] as metric of the impact of attributes for learning. Information gain of attribute *A* can be denoted as

$$\mathrm{Gain}(A) = \mathrm{Info}(D) - \mathrm{Info}_A(D),$$

Function Info() is defined as entropy in Shannon information theory. And $\mathrm{Info}_A(D)$ is the expected information required to classify a tuple from *D* based on the partitioning by *A*.

According to the above method, we can gain a decision tree that can reasonably perform the classification task. See Figure 7.

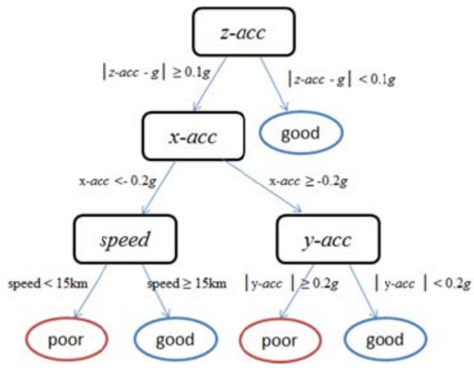

Figure 7. Decision Tree for road roughness detection

4.5 Result Annotation

Through the above processes we have gained a high-level context (i.e. knowledge) about the road roughness condition. We annotate this context on Google Map: Fig. 8 shows results from a single trace from road test in Haidian District of Beijing on April 15, 2011. The blue lines represent the vehicle traces and the red circles pinpoint poor road surface. Fig. 9 shows results from 10 vehicles on April 27, 2011, that predict the possible locations with poor road surface in Beijing downtown.

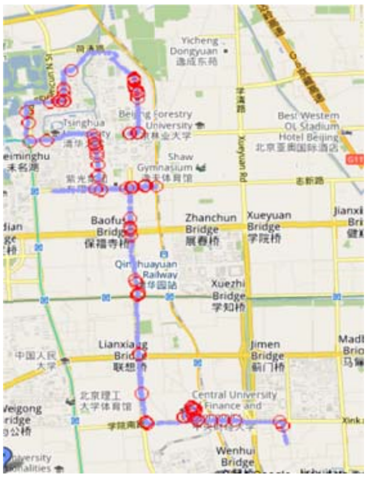

Figure 8. Single Trace Result Annotation

Figure 9. Multiple Traces Result Annotation

5. CONCLUSION

In this paper, we propose CAMS as a general framework to develop context-aware applications in participatory urban sensing. The ultimate goal of CAMS is to better understand and deal with the challenges in context acquisition, fidelity, dynamics and complexity. At the first time use CAMS in the road roughness case study in Beijing. We propose decision-tree based algorithm to classify normal and anomaly road surface conditions.

In further study, practical applications and engineering efforts are the driving forces of mobile sensing system research. The prevalence of sensor-embedded smartphone will greatly extend the special and temporal range of data acquisition. Also, other machine learning methods can be developed as building blocks of CAMS framework. More comprehensive phenomenon will be discovered, such as traffic jam pattern recognition, dynamics of urban temperature/humidity, and the correlation between air pollution and energy consumption, and so on. All of these applications are revealing great potential on mobile metropolitan sensing.

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