Context-Aware Computing: Opportunities and Open Issues

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1. EXTENDED ABSTRACT

A 2011 Gartner report [2] describes *context-aware computing* as a game-changing opportunity for enterprises to improve both productivity and profits. Context-aware computing is about making applications and content more relevant to a user's context, e.g., when and where the user is, thereby improving user experience. For instance, a coupon delivered to a user at a wrong time or at a wrong location is considered a nuisance. On the contrary, receiving a timely, usable coupon before purchasing a merchandise is a treat. Context-aware computing is not a new concept, but the ongoing mobile revolution makes it both necessary and feasible.

- Necessary because the mobile phone display is small and information must be delivered with much higher relevance and precision to meet user needs.
- Feasible because small, light-weight mobile devices allow users to almost always carry them around, and much can be learned via a phone about its user's habits and states.

Such contextual information can be used not only to improve content precision for search (information pulling), but also to make timely and relevant recommendations (information pushing). Context-aware computing can enable a paradigm shift in information retrieval and enterprise management from passively receiving information requests to proactively managing both information and the most appropriate context in which the information is delivered.

Context-aware computing involves first acquiring context and then taking context-dependent actions. For instance, a phone can sense a user's location and turn off its GPS unit to conserve power when the user enters a building, or it can collect EKG signals of a user and trigger an alert if the user's heart beats irregularly. Similarly, a restaurant can send a coupon to a user when that user is queued up in front of a nearby restaurant. The useful context can be divided into three categories: information on the user (knowledge of habits, emotional state, biophysiological conditions), the user's environment (time, location, co-location of others, social interaction), and the user's tasks (transportation mode, engaged tasks, general goals) [4]. Context-aware computing can be applied to benefit applications in many areas including but not

limited to *information retrieval, facility management, productivity enhancement*, in addition to the aforementioned three examples representing *power management, health care*, and *commerce*, respectively.

Let us use two foundational subroutines to help illustrate key technical challenges that context-aware computing comes up against. The first subroutine is *transportation-mode detection*, which detects a user's means of achieving mobility, e.g., walking, biking, taking a bus, taking MTR, etc.. The second one is *indoor localization*, which fuses signals of several modalities to estimate the indoor position of a user. Location is one of the most useful context. Though outdoor localization is considered a problem largely solved, solutions for indoor localization are still far from being satisfactory. These two subroutines provide essential movement-related contexts of which many applications can take advantage. *Indoor localization* predicts a user's location, and *transportation-mode detection* predicts the user's engaged task or intent at that location. For instance, when a user is stationary at noon in a shopping mall for a period of time, she is most likely in a restaurant or coffee shop. Furthermore, depending her secondary motion, *transportation-mode detection* can further tell if she is alone or engaging in a conversation. Similarly, a fast-pacing person in a shopping district may not express a strong purchasing intent, whereas a person dawdling around may very likely be looking for a merchandise and is therefore a target to issue a location-relevant coupon.

Transportation Mode

The design of a transportation-mode classifier aims to achieve high detection accuracy at low power consumption. Whereas the high-detection-accuracy goal has been attained by some studies (e.g., [3]), the goal of low power consumption has not been achieved by today's smartphones. To achieve the twin goals of high accuracy and low power consumption, we recently proposed a three-tier architecture consisting of computation modules located at *sensor hub, mobile client*, and *cloud server* [5]. These three tiers work in tandem to adapt to available resources and power. In particular, our sensor hub configures a gyroscope, g-sensor, compass, and barometer with a low-end coprocessor, which performs local computation without frequently interrupting CPU. During the implementation, we encountered two big-data mining issues.

1. *Big data, small footprint.* A consequence of training with big data is that it yields a large model file [?]. A large model file requires large storage and long classification time, both are undesirable to run on a sensor hub.
2. *Signal variance.* There are three major sources of signal variance for detecting movement: sensors, users, and ve-

hicles. Sensors manufactured by different vendors may exhibit slightly different error characteristics. Users of different genders, religions, cultures and builds may move differently. Road conditions and vehicle types/brands can also contribute to signal variance. Cross calibration is required to reduce such variances. When cross-calibration is infeasible because training data may not be available for all variance combinations, a machine learning algorithm must be able to still perform well at circumstances where the distributions of the training and the unseen data observe slightly different distributions.

Our preliminary work [5] addresses the above issues by trading a small percentage of classification accuracy (about 2%) for saving significant power (90%).

Location, Indoor

XINS is an indoor-localization architecture developed at Google [1]. XINS uses *particle filter* to continuously fuse signals from WiFi, motion sensors, and indoor map to predict a mobile device's indoor location. XINS, however, faces several technical challenges in achieving high location-prediction accuracy:

1. *Signal noise.* A high-end mobile phone today is already equipped with RF, motion, proximity, and light sensors. However, these low-cost sensors are prone to manufacturing defects, alignment biases, and environmental interferences. For instance, magnetometers often suffer from electromagnetic interference, and gyroscopes from PCB misalignment and temperature changes. Techniques in sensor calibration and error concealment, especially those not intrusive to users, are to be researched and developed.

2. *Secondary signals.* One major factor that hinders high accuracy in detecting user traveling direction and speed is the secondary signals that interfere with the primary signals. For instance, one could hold the phone steadily on hand while walking to view a map, and consequently, one's vertical motion signals for detecting footsteps are cancelled. One sitting at a coffee shop may make a call, and thus appears to be non-stationary.

Gyroscopes and accelerometers have been successfully used in submarines and missiles to facilitate dead reckoning. However, the movement of mobile phones and wearable devices is typically not smooth compared with that of submarines and missiles. To reduce the ill effect of signal noises, we proposed the Vibration Energy Model (VEM). VEM is based on *Equipartition theorem*, which states that energy is shared equally among all degrees of freedom. When a pedestrian walks, he usually swings his arms parallel to his walking direction. This swing motion can be considered as storing sufficient energy before being able to walk. Following the *Equipartition theorem*, pedestrians can use/store energy between walking/swinging. Therefore, VEM uses the signal of swinging energy as the key hint to predict the moving direction. Detecting moving direction in the energy domain avoids the error magnification problem of the spatial domain approach, which requires taking two integrals on the g-sensor signals and one integral on the angular acceleration. For the detailed specification of VEM, please consult [1].

There are two general approaches for deploying indoor localization. The first approach is to register all locations of WiFi access points (APs) and their power strengths. Given a set of APs scanned by a mobile phone and their signal strengths, the location of the mobile device can be estimated through triangulation. Since signals can be obstructed by walls and disturbed by pedestrians, this approach does not yield high accuracy. The second approach is to survey signal fingerprints at all locations. When a mobile device detects a fingerprint, its location can be predicted through finding matching fingerprints. Though this fingerprint approach can achieve higher accuracy, surveying fingerprints is a laborious task, and maintaining such a database requires periodical resurveys.

Crowd sourcing is a solution to address the site survey nightmare. Given an indoor map, crowd sourcing plots pedestrians' walking paths, and at the same time, collects WiFi fingerprints at walk-by locations on the map. With sufficient number of collected walking paths, a heat map of fingerprints can be created by performing averaging and outlier removals. Crowd sourcing can also be applied to facilitate the following tasks:

1. Annotating points of interest (POIs). With users' check-in record at a location, the name of that location can be annotated.

2. Predicting tasks at a POI. With a user's moving pattern (or lacking movement) at a location, and the nature of the location, we can predict if a user is e.g., dining, shopping, or pacing (waiting for friends).

3. Calibrating sensors. If a sensor provides data that deviates from the ground truth in a consistent way, the error can be used to calibrate the sensor to align to the ground truth.

Technical Issues

We shared our experiences in developing key subroutines of context-aware computing. The following issues closely related to the database community remain to be addressed to improve context signal acquisition and inference:

- *Sensor calibration and error concealment.* Non-intrusive calibration methods remain to be develop to reduce signal errors.
- *Big data, small footprint.* A small footprint is desirable to conserve the space and power of a mobile, wearable device.
- *Signal variance.* A classifier must be able to adapt to unseen data that observe a different statistical distribution from the training data.

2. REFERENCES

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