Pattern-Based Compressed Phone Sensing

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Abstract*—This paper presents an unobtrusive, energy-efficient approach to human activity sensing through the intelligent scheduling of built-in sensors on mobile phones and light-weight compressed sensing. We refer to this framework as pattern-based compressed phone sensing (P-CPS) where two challenging issues are studied, the energy drainage issue due to continuous sensing which may impede the normal functionality of the mobile phones and the requirement of active user inputs for data collection that may place a high burden on the user. The proposed P-CPS framework consists of two stages – training stage and sensing stage. In the training stage, a *Pattern Matrix (PM)* is constructed and an adaptive sensing scheme is used to update the PM automatically in order to keep records of a user's activity occurrences. In the sensing stage, P-CPS incorporates a Gaussian mixture model-based activity modeling and the adaptive sensing scheme for sensing scheduling. Compressed sensing (CS) is applied during the activity signal acquisition process. P-CPS uses a sparse binary measurement matrix which results in only simple matrix additions at the mobile side for energy efficiency purpose. Experimental results on driving activity sensing show that P-CPS can have, on average, the sensing scheduling accuracy about 70% but with 62.86% less energy consumption as compared to the continuous sensing.

I. Introduction

With the widespread popularity of mobile phones and the rich set of built-in sensors, mobile phones have revolutionized the way "sensing" can be performed. Collectively, these sensors have made available a variety of applications across different domains, including, for example, social networking, health care, and location based services [1], among which human centered mobile phone activity sensing has gained more and more attention. The work from Gonzalez et al. [2] published in *Nature* tried to study the basic laws that govern human motion using mobile phones. Huynh et al. [3] used topic models to realize the automatic discovery of such patterns in a mobile phone user's daily routine.

Depending on how much the user should be actively involved during the sensing activity, mobile phone sensing can be divided into *participatory sensing*, where the user actively participates in the data collection activity (i.e., the user manually determines how, when, what, and where to sample), or, alternatively, *opportunistic sensing*, where the data collection is fully automated without any user involvement [1]. Although opportunistic sensing relieves the burden placed on the user, it would require the phone sensors to continuously function which drastically reduces battery lifetime into a few hours, jeopardizing the usability of the phone. Participatory sensing leverages human intelligence into the sensing. The drawback is that the quality of data is dependent on participant's enthusiasm to reliably collect the sensing data and the compatibility of a person's mobility patterns to the intended goals of the application [1].

In this paper, we overcome these problems by proposing a pattern-based compressed phone sensing (P-CPS) framework for human-centered activity sensing. Since human-centered activity sensing targets at individual's activity, the sensing schedule can be made to correlate with the human activity pattern. In other words, mobile phone sensing should take advantage of the *context*. P-CPS first utilizes the recorded *Pattern Matrix (PM)* to build the activity pattern model. It then uses this model to update the future PM for sensing scheduling, which largely alleviates the resource consumption from continuous sensing. Compressed sensing (CS) is then applied during the time of activity sensing. CS has been widely used in the area of signal sensing and compression [4], [5] since it reduces the number of digital samples required to reconstruct from highly incomplete information, which is ideal for the mobile phones. For example, CS has been applied for human activity signals in [6], [7]. [8] utilizes a measurement scheduling matrix for soil moisture sensing as well as sensing scheduling, which share some common idea as our pattern matrix. However, CS requires a matrix-vector multiplication to obtain the observed data. Traditional CS uses DCT, Wavelet, or scrambled Fourier as a non-adaptive dense measurement matrix, which would put much computational burden on the mobile phone and introduce sensing overhead. We propose a sparse binary measurement matrix which results in simple matrix operation (i.e., only additions) at the mobile side for practical application.

To the best of our knowledge, this paper is the first to incorporate human activity patterns into mobile phone sensing using compressed sensing technique.

The rest of this paper is organized as follows. In Section II, we give the definition of the pattern-based activity and modeling as well as how to build the pattern matrix for sensing scheduling. In Section III, we introduce compressed phone sensing with details on how to apply it in the P-CPS framework. Sensing scheduling accuracy, smart phone energy consumption, and activity signal recovery results using P-CPS are shown in Section IV. Section V concludes the paper.

II. Pattern-Based Activities - Modeling and Realization

In this section, we first define "activity" and "pattern-based activity". We then present the mechanism to model the activity pattern used in P-CPS. We explain how to use the pattern matrix to incorporate the activity patterns and how to construct and maintain such a matrix for P-CPS.

A. Definition

We define the *human activity* (e.g., walking, driving, jogging) as a sequence of meaningful actions intended to achieve certain goals. We assume an activity is different from the actions or operations, where the latter usually last for very short duration while an activity generally consists of a sequence of actions. *Activity pattern* is related to an individual's activity but different from the activity itself. We define that an activity is pattern-based if: (1) it is a frequently occurring event, (2) it tends to have pattern over a long period of time, and (3) it is different from user to user. For example, for most people in the US, driving is a daily activity. However, the time period one drives and how long the driving activity takes place are different from person to person. This is one's driving pattern.

B. Modeling

In order for the smart phone to be able to predict the activity and thus perform sensing tasks, two pieces of information are essential: (1) *The granularity of an activity:* We consider an activity to be meaningful if its duration is longer than certain amount of time. In P-CPS we define the granularity of an activity as 5 minutes. Accordingly, we divide a day into 5-minute time slots, yielding totally $\frac{24\times60}{5} = 288$ slots. (2) *The temporal information of the previous activity:* The temporal information of the past activity is very useful for building the activity model and for prediction purpose. The temporal information can be collected in the form of time when the activity started and the duration of the activity.

Here, we define the *Pattern Matrix (PM)* of an activity which incorporates both the above information as follows.

Definition 1 (Pattern Matrix)**.** *A Pattern Matrix is a binary matrix with each column j representing a day and each row i, $(1 \le i \le 288)$, representing a time slot during that day, such that,*

$$PM(i,j) = \begin{cases} 0 & \textit{the activity does not occur} \\ 1 & \textit{the activity occurs.} \end{cases}$$

Therefore, each column of the PM records the temporal information of an activity happened over that day with the predefined activity granularity using binary indicators. By adding one column each day to the PM with predicted values based on the activity pattern model, we can predict future activities in order to schedule the mobile phone sensors for intelligent sensing.

In P-CPS, we use the Gaussian Mixture Model (GMM) to model the activity pattern. Generally speaking, a user tends to perform an activity at around one particular time of the day and the frequency of occurrence gradually decreases as time of the activity deviates from that favorite time. Thus the total number of activity occurrence at each time slot during a day over a long period of time would fit into a GMM. Figure 1 shows an example of modeling the driving pattern using the GMM.

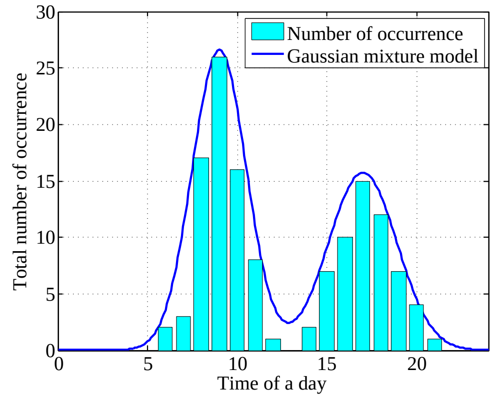

Fig. 1: An example of modeling the driving activity pattern using the GMM.

C. Pattern Matrix Construction and Maintenance

1) Training stage – Learning based adaptation: Initially, the PM is a 288×1 column vector and will be increased one column per day during the training stage. The length of the training stage can be defined arbitrarily, for example, 2 months in our experiment.

P-CPS uses a learning technique based on the theory of learning automata to control the sensing rate of the sensors. In particular, we use the *linear reward-inaction* [9] algorithm. Learning automata based techniques are defined in terms of *actions*, *probability* of taking these actions, and their resulting *success* or *failure*. In P-CPS, the only action taken is sensing from a sensor. The decision whether to sense or not at a time slot i is based on the probability p_i, which we refer to as *probability of sensing*. When a sensor conducts sensing that results in capturing an activity of interests, it is considered a *success*, otherwise, a *failure*. The probability of sensing is dynamically adjusted according to their previous success or failure rate, as formulated below:

$$p_{\{i+1,\cdots,i+n\}} = \begin{cases} p_i + \alpha(1-p_i) & \text{action is a success} \\ p_i - \alpha p_i, & \text{action is a failure} \end{cases}$$

where the action is taken at time slot i with sensing probability p_i, $0 < \alpha < 1$, and n is the number of time slots following the time slot i whose probability of sensing will be affected by the success or failure event at time slot i. We set $n = 10$.

At the beginning of each day, P-CPS will first randomly initialize one column of PM with probability values p_i $(0.1 \le p_i \le 0.9)$. We limit the lower bound to 0.1 to avoid very small sampling opportunity, which will potentially lead to miss an activity. We also limit the upper bound to avoid a too

00:00	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	
00:05	0	1	0	0	0	0	1	1	1	0	1	0	0	1	1	0	0	1	1	
00:10	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0	1	1	0	0	
00:15	1	0	0	0	0	0	1	0	1	1	1	1	0	0	0	0	0	1	1	
00:20	0	0	0	1	0	1	0	1	0	0	0	0	0	1	0	0	0	0	0	
00:25	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	
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…	…									…						…				
23:20	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	1	
23:15	0	0	0	0	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0	
23:20	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1	1	0	0	
23:25	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	
23:30	1	1	0	0	0	0	0	0	1	0	0	0	1	0	1	0	0	0	1	
23:35	1	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0	
23:40	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	1	0	1	0	
23:45	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0	1	0	0	0	
23:50	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	
23:55																				
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20

Day of observation Scheduling

Fig. 2: An pattern matrix and sensing scheduling.

aggressive sampling, which reduces the battery life. Based on the common sense that human beings are more active during day time, P-CPS intentionally places higher p_i values in the daytime slots (i.e., non-uniform randomization). Then during that day, P-CPS will perform activity sensing at a certain time slot, i, when p_i exceeds a threshold τ. The success or failure of this sensing (i.e., if during that time slot, it actually captures any activity of interest) will, on one hand, be used to update the probability of sensing of the subsequent time slots as formulated above; and on the other hand, update the current probability of sensing value to 1 (success) or 0 (failure). By adopting these mechanisms, the sampling rate adapts to the context of the user's activity pattern.

2) Sensing stage – Activity pattern model based scheduling: After the training stage, a GMM will be built based on the PM. We use two Gaussian mixtures and the Expectation Maximization (EM) algorithm to estimate the parameters used in the GMM model. Then at the beginning of each day, instead of randomly generating the probability value p_i, the probability p_i will be initialized based on the prediction from the pattern model. Then the adaptive sampling mechanism will be used to perform the sensing tasks as usual. Figure 2 shows the PM and the prediction of the sensing time.

III. Compressed Phone Sensing

In this section, we describe how P-CPS uses the Compressed Sensing (CS) technique during activity sensing to further reduce the amount of sampling.

A. Random Sensing

When mobile phone sensors are active for activity sensing during any 5-minute time slot, instead of keeping the sensors on for the whole 5 minutes, P-CPS randomly starts the sensors and keeps them active for approximately one minute. This can be thought of as applying another level of CS on the activity signal acquisition. The random sampled measurements can then be used to reconstruct the entire 5-minute signal with high precision as shown in our experiments. Depending on the level of accuracy and the number of data samples an application requires, different random sensing time can be chosen.

B. Generating Measurements

CS is a state-of-the-art data compression and reconstruction theory that exploits the fact that many natural signals are sparse or compressible in the sense that they have concise representations when expressed in the appropriate basis. Let Ψ be an $n \times n$ basis matrix and s be a sparse expression of the original signal $x \in \mathbb{R}^n$. Then x can be expressed as $x = \Psi s$. In the CS theory, the original signal x is projected to an $m \times n$ measurement matrix Φ, and the linear projections $y \in \mathbb{R}^m$ are then sent to a server. This measurement y is expressed as $y = \Phi x = \Phi \Psi s$, where Φ should be incoherent with Ψ.

On the server side, Φ and Ψ are known, since we assume that x can be sparsely represented in the basis Ψ, s can be estimated by solve the ℓ_1-norm minimization using linear programming:

$$\arg\min_{s} ||s||_1 \qquad s.t. \qquad y = \Phi \Psi s \tag{1}$$

Typically, CS uses random Gaussian, scrambled Fourier matrices as the measurement matrix Φ, however, a sparse binary measurement matrix has gained its reputation by being able to reduce the matrix multiplication to only addition thus reducing the total number of operations. The sparse measurement matrix used in P-CPS is based on the adjacency matrix of the high-quality expander graph, with guaranteed CS recovery [10]. The design of the sparse binary matrix is detailed in [11]. We also choose a discrete cosine transform (DCT) as the activity signal basis matrix Ψ at the server side to ensure that the signal holds certain level of sparsity.

IV. Experimental Results

We implement an application on the Google Nexus S smart phone that uses the accelerometer sensor to perform the driving activity sensing and collect data from 6 subjects across various time frames (e.g., school time, weekend, summer time, etc.). All subjects are college students, each of who collects data for more than 70 days, with the longest one about 8 months.

A. Performance Metrics

We use three metrics to evaluate the effectiveness of the proposed P-CPS framework: *accuracy*, *energy*, and *recovery error*. The accuracy is measured in terms of the percentage of captured driving activity within each 5-minute time slot each day. The energy consumption the amount of energy consumed by P-CPS. For evaluation purpose, we compare the energy consumption of three sensing schemes, continuous sensing of the accelerometer sensor, pattern-based scheduling (i.e., same as P-CPS sensing stage) but using continuous sensing (Pattern non-CS) during the 5-minute time slot, and P-CPS. We make certain that the mobile phone is under the same settings, sensors and applications). The recovery error is measured based on the Root Mean Square Error (RMSE) of the accelerometer signal.

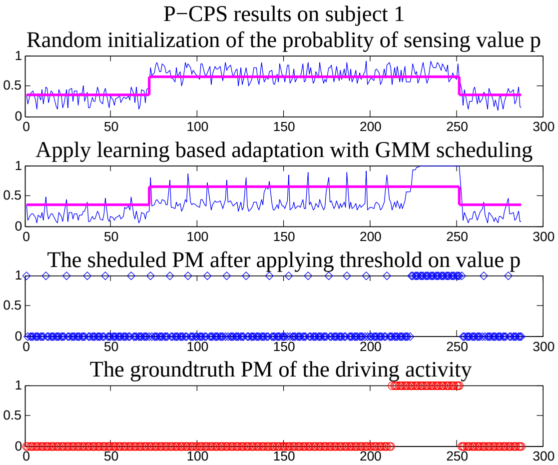

Fig. 3: The results on P-CPS initialization and scheduling.

Stage	Subj. 1	Subj. 2	Subj. 3	Subj. 4	Subj. 5	Subj. 6
Training	66.67%	56.10%	42.85%	63.89%	53.33%	53.57%
Sensing	81.06%	72.50%	71.11%	78.26%	65.22%	75%

TABLE I: Averaged P-CPS training and sensing stage accuracy on 6 subjects using GMM with two mixture components, with 50 days during training stage, 20 days during sensing stage, and $\alpha = 0.5$.

B. Accuracy

For all the subjects, we use 50 days for the P-CPS training stage and 20 days for the sensing stage. We also randomly initialize the p_i $(1 \leq i \leq 288)$ in the range $[0.1, 0.5]$ for the night time slots and $[0.5, 0.9]$ for the day time slots. The threshold τ is set to be 0.35 and 0.65, respectively. Table I shows the average accuracy during our experiment. We explore the performance of learning using different α, and set $\alpha = 0.5$ to balance the accuracy and sensing energy in our experiment. Figure 3 shows the results on P-CPS initialization and scheduling.

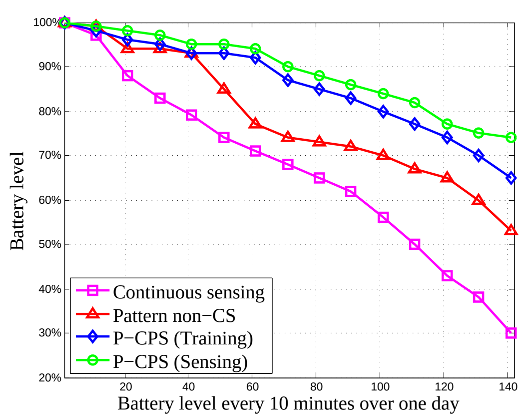

Fig. 4: Energy consumption of different sensing schemes.

C. Energy Consumption Comparison

Figure 4 demonstrates the mobile energy consumption using different sensing schemes. We observe that P-CPS can save 62.86% of energy than continuous sensing and 39.62% of energy than pattern-based normal sensing.

D. Recovery Accuracy

In the experiment, we collect the accelerometer signal in x-, y-, z- axis separately at random one-minute duration when the mobile sensor is active in a particular 5-minute time slot. The collected signal if of dimension 3000. We use the famous ℓ_1-magic matlab package for CS recovery. The CS measurement matrix Φ is a 600×3000 sparse binary matrix (i.e., the measurement ratio m/n is 0.2, and only 600 measurements will be sent to a sever for recovery). The recovered accelerometer signal has an average accuracy of approximately 0.0189 ± 0.014 NRMSE for the 20 sensing days of driving activity, which is very close to the original accelerometer signal.

V. Conclusions

In this paper, we presented the P-CPS framework, a pattern-based compressed phone sensing mechanism, where an activity pattern matrix was constructed and adaptively modified to control the scheduling of active sensing. During the period of active sensing, CS was applied to further reduce samples acquired. Experimental results showed that P-CPS had a sensing scheduling accuracy about 70% while the smart phone energy consumption using P-CPS is 62.86% less than that of using continuous sensing.

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