Poster Abstract: Ear-Phone-Assessment of Noise Pollution with Mobile Phones

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Abstract

Noise map can provide useful information to control noise pollution. We propose a people-centric noise collection system called the Ear-Phone. Due to the voluntary participation of people, the number and location of samples cannot be guaranteed. We propose and study two methods, based on compressive sensing, to reconstruct the missing samples.

Categories and Subject Descriptors

C.m [**Computer Systems Organization**]: Miscellaneous–*Mobile Sensing Systems*

General Terms

Design, Experimentation, Performance

Keywords

Noise Map, Compressive Sensing, People-Centric Sensing

1 Introduction

The negative impacts of environmental noise on human health and quality of life are undisputed [2]. Santini et al. [4] have recently proposed the deployment of wireless sensor network (WSNs) to monitor noise pollution, but deployment cost of static WSNs will be costly.

Several research projects (e.g. [3]) suggest an alternate approach of using microphones of mobile phones as inexpensive noise pollution sensors. Mobile phones can also be recharged and possibly calibrated with the assistance of its user. However, people-centric sensing cannot strictly guarantee the availability of data samples, since it relies on the voluntary participation of people whose presence is irregular in space and time. Furthermore, volunteers have priority in using their mobile phones for conversation. Therefore, a people-centric noise monitoring application poses a fundamental problem of signal reconstruction from incomplete and random samples. We address these challenges. Our contributions are:

1. We present a sensing system, Ear-Phone, to recover a noise map from incomplete and random samples in the people-centric sensing platform.

2. Within Ear-phone we investigate two sensing strategies, a) projection method: each volunteer sends one aggregated noise level to the central server and b) raw-data method: each volunteer sends noise samples without aggregation. We report sampling requirements, reconstruction accuracy and communication overhead tradeoff of these two sensing strategies.

2 Ear-Phone System

Our Ear-Phone architecture is shown in Figure 1. The signal-processing unit is used to compute the loudness level over one second from acoustic samples collected from the microphone sampled at 16 kHz. An A-weighting filter is then applied to the loudness level and the equivalent sound level $LA_{eq,1s}$ is computed. Computed LA_{eq} 1s is then attested with the location and time collected simultaneously from the GPS receiver. The Communication unit finally transmits the information to the central server. Once information is sent to the central server, the reconstruction unit recovers the missing data and generates the noise map.

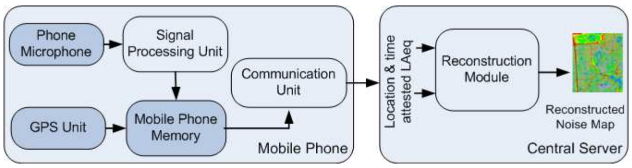


Figure 1: Ear-Phone architecture

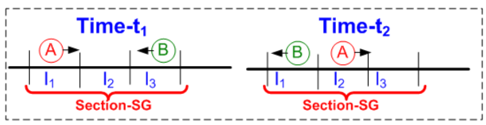
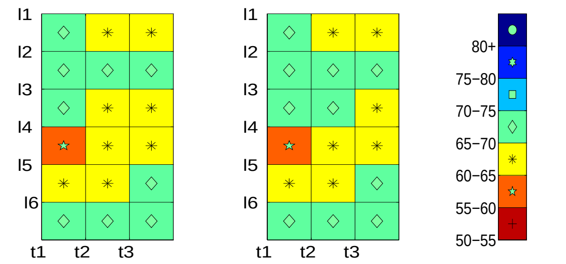


Figure 2: People-Centric sensing

2.1 Signal Reconstruction

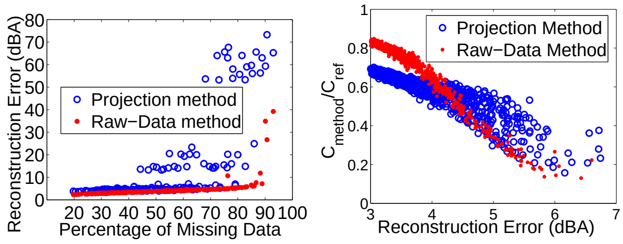
We exploit the theory of Compressive Sensing (CS) to reconstruct the noise map from incomplete samples. CS reconstructs compressible signals with significantly fewer samples

This work is supported by ARC Discovery grant DP0770523. Part of this work is done when Mr. Rana is a visitor at CSIRO.



(a) **3 $LA_{eq,1s}$ snapshots of 6 locations** (b) **Reconstruction of Figure 3(a)** (c) **Scale(dBA)**

Figure 3: Noise map reconstruction



(a) **Reconstruction accuracy VS sampling density** (b) **Reconstruction accuracy VS communication overhead**

Figure 4: Raw-data VS Projection method

than required by the traditional sampling methods. A distinctive feature of compressive sensing is that it uses projections to collect information. The projection of the vector $x \in \mathbb{R}^n$ on a projection vector $\psi \in \mathbb{R}^n$ is defined by the inner product $\psi^T x$. We propose two sensing strategies based on two different methods of doing projections. Let us illustrate the sensing strategies with an example.

Let us consider the trajectories of volunteers, A and B along three segments: ℓ_1, ℓ_2 and ℓ_3 of section SG of a street (see Figure 2). Assume that at time t_1 and t_2, volunteer A collects noise samples in segments ℓ_1 and ℓ_2, and B collects samples in segments ℓ_3 and ℓ_1 respectively. Note that the complete noise level in section SG, during time t_1 and t_2 can be represented as a vector $x = [d(\ell_1,t_1),\ldots,d(\ell_3,t_2)]^{\mathrm{T}}$, where $d(\ell,t)$ is the noise level at locations $\ell = \ell_1,\ell_2,\ell_3$ and time $t = t_1,t_2$. In this paper we refer to the vector x as a noise profile. Samples collected by A and B can be represented as vectors x_A and x_B respectively.

In the projection method, A multiplies his measurement vector x_A with a projection vector $\phi_A = [\phi_A^1, 0, 0, 0, \phi_A^5, 0]$ (here ϕ_A^1, ϕ_A^5 are drawn from the standard Gaussian distribution.) and sends the projected value, $y_A = \phi_A^T x_A$ to central server. In the raw-data method, A directly sends his measurements to the central server where the projection vectors for A's data is regenerated as $\phi_A = [1,0,0,0,0,0;0,0,0,0,1,0]$. Finally, the reconstruction module accumulates the projected values and uses Compressive Sensing [1] to recover the missing data. We compute the root mean square (RMS) error to evaluate reconstruction accuracy and compute communication cost from the number of bytes transmitted by each of the sensing strategies. Note that the projection method saves communication cost from data aggregation, but due to aggregation some information is lost.

3 Initial Pilot and Future Work

We installed the mobile phone component on 6 HP iPAQ 6965 mobile phones (MobSLM) and conducted 4 outdoor experiments by placing them in 6 equally spaced locations along a major road with the microphone pointed towards the road measuring $LA_{eq,1s}$. We used the recorded noise levels as reference noise profiles and simulated both sensing strategies to reconstruct them. In Figure 3(a) we present 3 snapshots (t1–t3) (from one of our experiments) of $LA_{eq,1s}$ over 6 spatial locations (l1–l6) and Figure 3(b) is the corresponding reconstruction. Note that the reconstructed snapshots are very close to the reference. Approximately 47% of measurements were used for the reconstruction which produced < 3 dBA RMS error (a difference of 3 dBA is non-perceptible by human being). Averaging the reconstructed snapshots over a given time period will produce a noise map which can be overlaid on an Internet map.

Figure 4(a) demonstrates the sampling requirements and reconstruction accuracy trade-off of the sensing strategies. On average, using only 50% of information, the raw-data method reconstructs the noise profile within 3 dBA reconstruction error. In addition, it requires 30% less information compared to the projection method.

Figure 4(b) reports the communication cost and reconstruction accuracy trade-off of the sensing strategies. Let C_{method} be the number of bytes transmitted by either raw-data or projection method and C_{ref} be the number of bytes transmitted, if $LA_{eq,1s}$ samples from the complete noise profile are transmitted. We achieve 3 dBA reconstruction accuracy when $C_{project}$ is much smaller (about 35%) than C_{ref}, but C_{raw} being only 15% smaller than C_{ref} achieves the same accuracy. However, with the increase of missing information, communication cost of the raw-data becomes smaller than the projection method.

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