Poster Abstract: Compressed Sensing of Audio Signals in a Wireless Sensor Network

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***Abstract*—Compressed sensing is an attractive compression scheme due to its universality and lack of complexity on the sensor side. In this work we demonstrate how it could be used in a wireless sensor network. We consider a sensor network that tracks the location of a subject wearing a device that periodically transmits an audio signal. Through simulations and measurements of a simple system, we illustrate that dramatic compression can be acheived.**

I. Introduction

Compressed Sensing (CS) [1] [2] seeks to represent a signal using a number of linear, non-adaptive measurements. Usually the number of measurements is much lower than the number of samples needed if the signal is sampled at the Nyquist rate, thus providing the benefits of reduced storage space and transmission bandwidth due to the phenomenal compression achieved. These features make CS an ideal candidate for use in wireless sensor networks (WSNs), where transmissions must be minimised in order to conserve limited power resources.

If the signals appearing at each sensor are jointly sparse [3], then this may be exploited by suitable reconstruction algorithms [4] to minimise total transmissions in the WSN. Other work in single-sensor CS has shown that if the goal is signal *detection* rather than reconstruction, further reduction in measurements is possible [5]. We combine these two results to show that dramatic reductions in data transmissions in a WSN can be acheived.

II. System Architecture

We consider a WSN that is used to track the location of a subject wearing a tracking device that periodically transmits an audio signal. The WSN would be arranged in some cell-like structure in an outdoor setting, or else the cells could be rooms of a large building similar to the system considered in [6]. We assume that each sensor has very limited computational ability, and simply transmits its readings to a data fusion centre (DFC).

As we wish to use CS detection algorithms in the DFC to minimise the number of required transmissions, our audio signal must be very sparse, and our system uses short pulses of a single frequency. This also ensures that the signals appearing at each sensor are jointly sparse, allowing us to use simultaneous orthogonal matched pursuit (SOMP) [4] along with the incoherent detection and estimation algorithm (IDEA) [5] in the DFC to detect the presence of a signal.

III. Simulation Results

Our simulation model consists of one cell of L microphone sensor nodes arranged equally around a circle. We assume the signal at each microphone is only a delayed and attenuated version of the signal at the sound source. The interested reader is directed to our earlier work [7] for more details on our audio model. From the N samples taken at the Nyquist rate at each sensor node, M are randomly selected and transmitted to the DFC. Note that with special hardware this could be done in a single process known as Random Sampling [8].

The DFC then uses these LM samples to detect whether or not there is a desired signal in the cell using SOMP and IDEA, and if so then estimate it. Figure 1(a) & (b) show the results of a simulation of the detection and estimation performance for a 10×10 metre cell. Curves are given for 1, 2 and 4 sensor nodes at a signal to noise ratio (SNR) of 40dB, and it is evident that increasing the number of sensors decreases the number of samples–and therefore transmissions–required per sensor node. For instance, with 4 sensors and a probability of error less than 10^{-2}, only 3 samples are required for detection and 7 for estimation. As $N = 128$, this is equivalent to compressions of 98% and 95%, respectively. Note that this requires extremely little computation on the part of the sensor node.

IV. Measured Results

Our experimental set-up consisted of two microphones five metres apart and a sound source between them. Pulses of different frequencies were played and recorded at each microphone. The sound source was placed at various points between the microphones.

We also simulated this configuration, but note that the experiment was performed in a highly-reflective 6×3 metre room and thus there was significant reveberation, which is not taken into account in the simulation. Nevertheless, the results in Figure 1(c)-(f) show that there is good agreement between the simulated and measured results.

The measured results are particularly encouraging as they indicate that these techniques are very suitable for indoor use and that reverberation caused by walls, floors and ceilings does not degrade performance significantly; only two samples from both sensor nodes provide a probability of detection error less than 10^{-2} and one more sample reduces this to less than 10^{-3}.

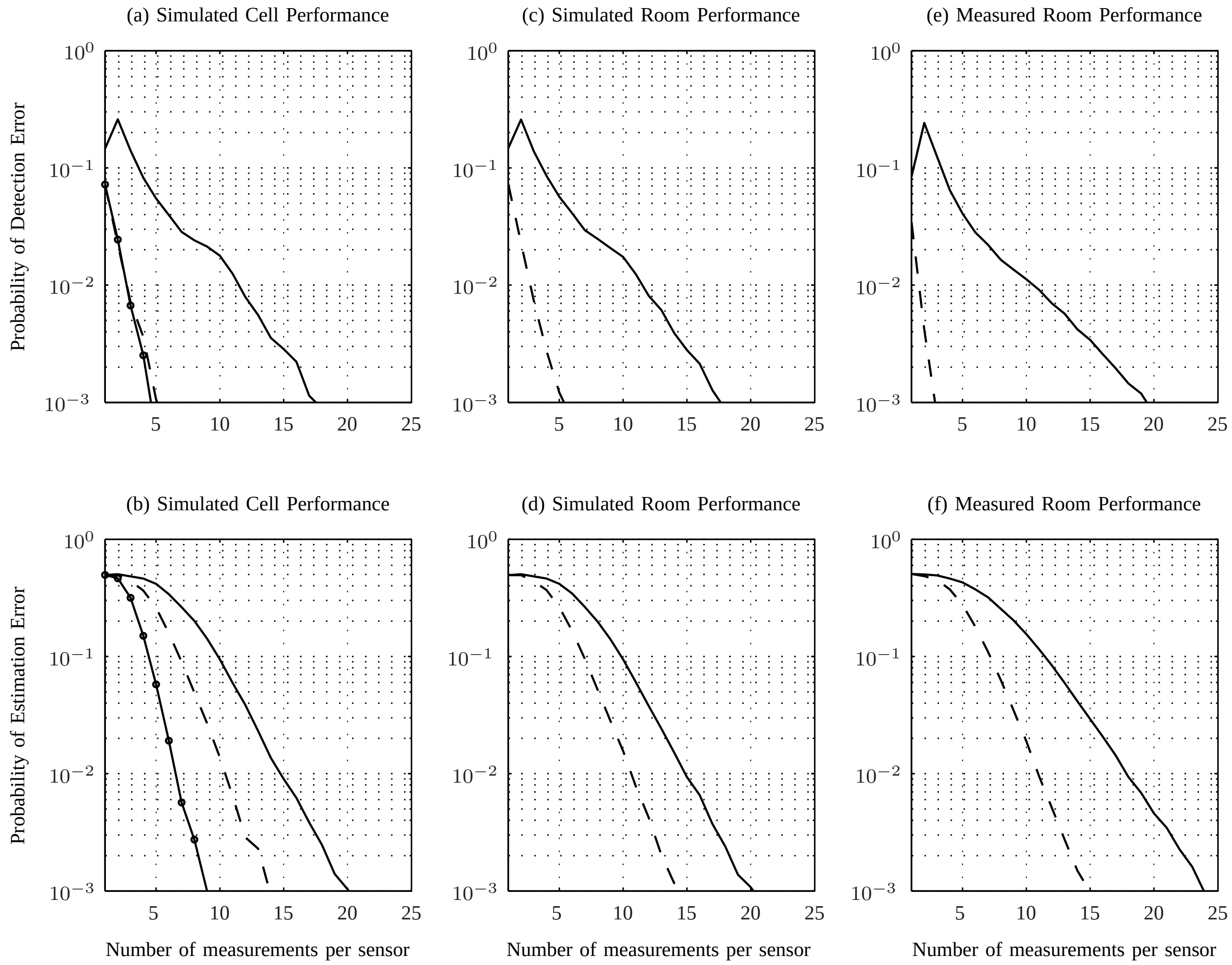

Fig. 1. Probability of detection and estimation error for signals recorded by a multi-sensor system. Results for a 10×10 metre cell are shown in (a) &(b), and a 6×3 metre room in (c)-(f). The solid line is the performance using one sensor, the dashed line with two sensors, and the dotted line with four sensors, however this only appears in (a) & (b). The Nyquist rate is 128 samples per sensor.

V. Conclusions

Through simulations and measurements, we have shown that CS and IDEA can be used in a detection and estimation audio WSN to dramatically reduce the number of transmissions to the DFC. These algorithms require only minimal processing on the sensor side, and only moderate computation in the DFC.

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