Data acquisition for motion recognition on mobile platforms via compressive sensing

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Abstract. This paper addresses the challenge of energy efficiently acquiring data on mobile platforms in order to recognize human motion. The method presented is based on the theory of compressive sensing and experimental results show that a significant reduction of the number of needed samples, in comparison to common methods, is possible.

1 Significance

There are many situations in which it has become necessary to acquire human motion data on a mobile device, especially for logging and offline processing. An application example where sensor data is continuously sampled and processed offline is SenseCam [1] or other activity logging applications such as calorie expenditure calculation applications. For a motion to be recognized, a signal has to be acquired and usually this process follows the Shannon criterion: the sampling frequency has to be at least twice the maximal frequency contained in the signal. Since it is not known a priori which signals are to be recorded (e.g. which activities occur during an ordinary day using acceleration sensors), there has to be a high enough a priori sampling rate to also capture high frequency motion. As this is energy consuming, we propose to sample the data following the compressive sampling theory with reduced energy consumption during the logging phase and then reconstruct offline on a non resource constrained device. This could be compared to the approach of modern GPS cameras that log the raw signal and then calculate the position offline on a home PC where enough computational power is available.

We verified our approach using well-known human motion data [4] as well as own data sets.

2 The sampling method

In order to reduce the number of samples, we make use of the theory of compressive sensing, a fast growing field of research. This theory states that a significant reduction can be achieved for signals that are known to be sparse in an orthogonal basis, cf. [2] and [3] for further details.

Since the human motion is often repetitive, one can assume that the signal that is to be acquired for motion recognition is sparse in the Fourier basis. That is, many but a few of its frequencies are (close to) zero. By acquiring only the much smaller number m instead of n samples of a signal $f \in \mathbb{R}^n$ in the time domain, f can still be perfectly recovered by solving an ℓ_1-minimization problem. This computationally demanding recovery process is recommended to be done on a desktop machine, thus implying a shift of energy consumption away from the mobile device.

A key concept of compressive sensing is that the samples have to be acquired uniformly at random, see [2]. In order to overcome the difficulty of a uniform selection for signals that are continual in the time domain, we propose a sampling strategy that is based on the Bernoulli Model introduced in the proof in [2].

Suppose we would normally sample at all frequent positions. Then we suggest to sample at each of them only with a probability $\tau = m/n$, with m and n complying with the constraints given in [3]. We emphasize the practicability of this Bernoulli strategy for signals that are continual in the time domain.

3 Experimental results

Without loss of generality, we may assume that the considered data for testing the above method was recorded with a frequency of 20Hz where further downsampling was limited by the Nyquist theorem.

As a proof of concept, we reduce the sampling rate even further, comparing the signal-to-noise ratios of our approach and of the conventional downsampling method (fig. 1). As an example, by observing each sample only with a probability of 0.25 and recovering the signal from these, we cut the sampling rate by 75% (fig. 2). The signal is well enough recovered by applying the NESTA algorithm [5]. Therefore, any subsequent recognition or machine learning tool chain (e.g. for activity recognition, or calorie expenditure calculation) can use the data acquired following the compressive sensing approach.

Note, that an exact recovery of the signal may not be required for identification purposes of a specific motion.

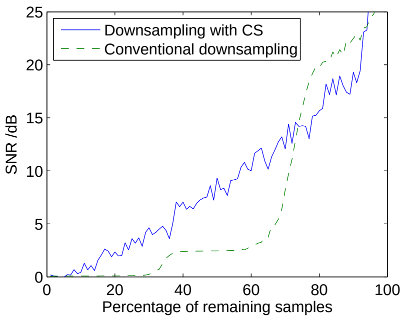

Fig. 1. SNR ratios for sampling rates below the Nyquist rate with compressive sensing (CS) and conventional downsampling

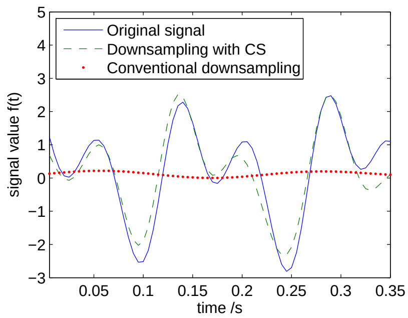

Fig. 2. An example section of the signal downsampled by factor 4 with compressive sensing and with the conventional method, compared to the original signal

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