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A neural algorithm for the non-uniform and adaptive sampling of biomedical data

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ABSTRACT

Background and objective: Body sensors are finding increasing applications in the self-monitoring for health-care and in the remote surveillance of sensitive people. The physiological data to be sampled can be non-stationary, with bursts of high amplitude and frequency content providing most information. Such data could be sampled efficiently with a non-uniform schedule that increases the sampling rate only during activity bursts.
Methods: A real time and adaptive algorithm is proposed to select the sampling rate, in order to reduce the number of measured samples, but still recording the main information. The algorithm is based on a neural network which predicts the subsequent samples and their uncertainties, requiring a measurement only when the risk of the prediction is larger than a selectable threshold.
Results: Four examples of application to biomedical data are discussed: electromyogram, electrocardiogram, electroencephalogram, and body acceleration. Sampling rates are reduced under the Nyquist limit, still preserving an accurate representation of the data and of their power spectral densities (PSD). For example, sampling at 60% of the Nyquist frequency, the percentage average rectified errors in estimating the signals are on the order of 10% and the PSD is fairly represented, until the highest frequencies. The method outperforms both uniform sampling and compressive sensing applied to the same data.
Conclusion: The discussed method allows to go beyond Nyquist limit, still preserving the information content of non-stationary biomedical signals. It could find applications in body sensor networks to lower the number of wireless communications (saving sensor power) and to reduce the occupation of memory.

1. Introduction

There are applications in which sampling at the Nyquist frequency is not efficient. For example, sparse signals are decomposed using a few significant components in compressive sensing (CS) [1]. Reducing the sampling rate is useful when many body sensors are used to monitor continuously the lifestyle of a healthy person or the condition of sensitive people [2]. Sensors are lightweight, non-invasive, wearable or embedded in cloth and they include a wireless communication with a storage and decision making system. Many physiological data can be sensed, e.g., acceleration, bioelectric activity, blood pressure, galvanic skin response, and breathing [3]. Monitoring these data supports the individual self-assessment which allows to develop a personalized health care that helps healthy people to maintain their well-being [4]. Moreover, many diseases can benefit from a continuous monitoring, like cardiovascular problems, diabetes, Alzheimer's and Parkinson's diseases, renal failure, chronic obstructive pulmonary disease, post-operative conditions, stress or sudden infant death syndrome [5]. The remote patient monitoring could allow a rapid intervention when needed, developing an individualized care [6], with positive effects on the management of clinical services and on the quality of life of patients [7]. Many additional applications of body sensors are found, e.g., in military monitoring, interactive gaming [8], recognition of dietary activity [9], rehabilitation [10], personal information sharing and secure authentication [11].

Some recorded signals can show burst activity, reflecting the alternation of periods in which the investigated physiological system is either silent or active: for example, surface electromyogram (EMG) during cyclic tasks [12] or in pathological conditions (e.g., motor tremor induced by epileptic seizures [13]); electrocardiogram (ECG), with the QRS complex including most of the high frequency content [14] (unless pathological behaviors arise [15]); electroencephalogram (EEG), when the brain is performing different tasks or in pathological conditions (e.g., seizure

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in epileptic patients [16]); body acceleration during different activities [18] or in pathological conditions [19].

When data contain bursts, a high sampling rate is required if a uniform sampling is adopted, even if there are portions of the signal which could be down-sampled without loss of information. A non-uniform sampling, using a high sample rate only during the bursts, would allow both memory and energy saving (very important for wireless sensors, which are supplied with scarce resources [20]).

A predetermined non-uniform sampling schedule cannot be established for biomedical applications, but the sampling should be adaptively defined on the basis of the data. Adaptive techniques, like AZTEC, CORTES, SLOPE, or Fan [21], have been developed specifically for ECG data compression. They can reduce considerably the number of acquired samples by a non-uniform sampling schedule, but they do not allow a real time modulation of the sampling frequency, as they require to measure each sample in order to decide if to keep it. A real time adaptive solution was proposed in [14], increasing the sampling rate when the signal curvature was high. The method showed higher performances than uniform sampling, but a-priori knowledge on the signal was required, limiting versatility [22]. In this respect, CS is considered more generally applicable [22], showing low compression ratio (CR, ratio between number of acquired versus original samples) and good accuracy [23,24]. However, it recovers the signal by an offline procedure applied on time epochs, introducing a delay. On the other hand, a real time adaptive sampling schedule could allow to save energy (to sample and transmit data) and to implement simple decision making control even on the sensor (e.g., a fall detector based on a threshold on the body acceleration). Thus, a versatile adaptive sampling algorithm could provide an important contribution.

The method proposed in [20] increased automatically the sampling rate when the investigated signal became unpredictable or provided high frequency contributions. A conceptual framework was discussed in [20], showing different general applications, but without optimizing the algorithm on specific data and the under-sampling was not measured relative to Nyquist frequency (problem affecting also the literature on CS applied to biomedical data [1], where approximation errors at specific CR are often provided without caring about the possible over-sampling of the original signal; see Discussion for details). The present work investigates these open issues. The algorithm proposed in [20] is improved, by an automatic tuning on the data, based on an offline analysis of a training set. The adaptive algorithm is compared with uniform sampling and CS with the same CR, when applied to different biomedical signals sampled at the Nyquist frequency: EMG, ECG, EEG and body acceleration.

2. Materials and methods

2.1. Adaptive sampling algorithm

The adaptive sampling is based on a prediction algorithm and on its application to estimate the uncertainty of a predicted sample. It can be split into three parts:

1. selection of optimal predictors (based on the theory of time series embedding, Section 2.1.1);
2. training of an adaptive algorithm to predict the next sample (a multi-layer perceptron, MLP, was used, Section 2.1.2);
3. real time schedule of the sampling rate (based on the uncertainty of the prediction, Section 2.1.3).

2.1.1. Time series embedding

Embedding theory was applied to the data [25–27]. Specifically, the time series were supposed to be extracted from a deterministic physiological system described by a set of unknown deterministic rules

$$\frac{d\vec{x}}{dt} = \vec{F}(\vec{x}) \tag{1}$$

where $\vec{x}$ is the vector of state variables of the system and $\vec{F}$ is a set of functions called the vector field (defining the evolution of the state variables), which was assumed not to be an explicit function of time (i.e., the system was assumed to be autonomous). The recorded time series $y(t)$ (where t from now on is a discrete time variable) was assumed to be extracted from the system through a measurement process described by an unknown function $g(\cdot)$ of the state variables:

$$y(t) = g(\vec{x}(t)) \tag{2}$$

Given a single measurement, a vector of time delayed versions (delayed coordinates) was built [25]

$$\vec{Y}(t) = \begin{bmatrix} y(t) \\ y(t-\tau) \\ \vdots \\ y(t-(m-1)\tau) \end{bmatrix} \tag{3}$$

where the time delay τ was chosen so that two delayed coordinates provided different information and the number m of elements of the vector is called the embedding dimension (as it is the dimension of the so called phase space in which the trajectory $\vec{Y}(t)$ is embedded) [25–27].

The time delay τ and the embedding dimension m were computed as follows.

- Time delay. The mutual information of the original and delayed data was computed:

$$\mathrm{MI}(\tau) = \int_A \int_B P_{AB}(a,b) \ \ln\left(\frac{P_{AB}(a,b)}{P_A(a)P_B(b)}\right) da\,db \tag{4}$$

  where the time series $y(t)$ and $y(t-\tau)$ are considered as random variables A and B, respectively, with joint probability density $P_{AB}(a,b)$ and marginal probabilities $P_A(a)$ and $P_B(b)$, respectively. The minimum between the delays corresponding to the first local minimum or to a 90% decrease of $\mathrm{MI}(\tau)$ was selected as the time delay τ of the delayed coordinates.
- Embedding dimension. Cao's method was used [27,28]. It is based on the number of points of the trajectory, described by the vector in (3), which are neighbors of other points of the trajectory itself. When increasing the embedding dimension by adding one element to the vector (3), neighboring points which were close only due to the projection of the trajectory in a low dimensional space (false near neighbors) may turn away. Thus, the number of neighboring points decreases by increasing the embedding dimension, till false neighbors are present. The minimum phase space dimension allowing to remove the false near neighbors was selected as the embedding dimension m: it allows to identify uniquely the dynamics of the trajectory and possibly to predict it. Specifically, Cao's method investigates the following function of the embedding dimension [28]

$$E1(m) = \frac{E(m+1)}{E(m)}, \quad \text{where } E(m) = \frac{1}{N-m\tau}\sum_{i=1}^{N-m\tau} \frac{\|Y_{m+1}(i) - Y_{m+1}(n(i,m))\|}{\|Y_m(i) - Y_m(n(i,m))\|} \tag{5}$$

  where N is the number of considered samples of the time series, $\|\cdot\|$ is the absolute distance norm, $Y_m(i)$ is the ith sample of the reconstructed vector with embedding dimension m and $n(i,m)$