

# A Wearable Device for Online and Long-Term ECG Monitoring

Marco Longoni<sup>1</sup>, Diego Carrera<sup>1</sup>, Beatrice Rossi<sup>2</sup>,  
Pasqualina Fragneto<sup>2</sup>, Marco Pessione<sup>2</sup>, Giacomo Boracchi<sup>1</sup>

<sup>1</sup> Politecnico di Milano, Milan, Italy

<sup>2</sup> STMicroelectronics, Agrate Brianza, Italy

## Abstract

We present a wearable device able to perform online and long-term monitoring of ECG signals, and automatically detect anomalous heartbeats such as arrhythmias. The core of our solution are user-specific dictionaries, which are learned every time the device is positioned. Anomalies are detected via an optimized sparse coding procedure, which assesses the conformance of each heartbeat to the user-specific dictionary. User-specific dictionaries are adapted during online monitoring, to track heart rate variations occurring during everyday activities. Perhaps surprisingly, dictionary adaptation can be successfully performed by transformations that are user-independent and learned from large datasets of ECG signals.

## 1 Introduction

In the last few years there has been a flourishing of smart-watches and bracelets able to monitor health parameters. Due to their limited sensing apparatus, these devices can not be used to ease the transitioning from hospital to home/mobile monitoring: as an example, the heart rate is often the only ECG measure provided. We present the *Bio2Bit-Dongle*, a prototype of wearable device developed by STMicroelectronics that features a better sensing apparatus and implements advanced machine learning algorithms to analyze the heartbeats shapes of each specific user. These algorithms have been designed to run online on a low-power dongle, to detect anomalous heartbeats, including dangerous arrhythmias, in a long-term monitoring scenario.

The Bio2Bit-Dongle is composed of the *Bio2Bit Move* [Gentile *et al.*, 2017] plugged on an adjustable and flexible chest strap, which acquires and transmits via Bluetooth Low Energy (BLE) the ECG signals, and of a low-power *dongle* (Section 3) that analyzes in real time the received signals. In particular, the dongle adopts a data-driven model describing the heartbeats' morphology of the current user, and detects as anomalous any heartbeat that does not conform to that. The anomaly-detection

algorithm [Carrera *et al.*, 2016] has a very low computational and battery requirements, which can be steadily executed on the considered low-power dongle. Online monitoring allows to raise timely alerts at each anomalous heartbeat, or to store these for further inspection.

Since the heartbeat morphology depends on the electrodes locations [Hoekema *et al.*, 2001] and anomalies can be very subtle, the user-specific model has to be learned every time the Bio2Bit Move is positioned. To this purpose, a few minutes of ECG signals, acquired in resting conditions, are enough to learn the user-specific model on any smartphone or on a powerful dongle (e.g., a smart-watch). Such a customization is not enough to enable long-term monitoring, since during everyday activities the heart rate changes and heartbeats get consequently transformed. Thus, the dongle estimates the current user heart rate, and adapts the learned model accordingly [Carrera *et al.*, 2017]. Figure 1 describes the Bio2Bit-Dongle and the monitoring procedures.

## 2 ECG Monitoring Algorithms

In what follows we describe the algorithms we designed to perform ECG monitoring on the Bio2Bit-Dongle.

**Anomaly Detection:** Pursuing a universal approach to anomaly detection [Chandola *et al.*, 2009], we learn a model [Bengio *et al.*, 2013] providing meaningful representations of the normal heartbeats for each specific user, and we detect as anomalous any heartbeat that does not conform to the learned model. In particular, we learn for each user  $u$  a dictionary  $D_u \in \mathbb{R}^{p \times n}$  such that any normal heartbeat  $\mathbf{s} \in \mathbb{R}^p$  can be well approximated by a sparse representation [Bruckstein *et al.*, 2009], i.e. a linear combination of few columns of  $D_u$ . We learn  $D_u$  from a training set of heartbeats acquired in resting conditions using the KSVD algorithm [Aharon *et al.*, 2006]. Thus, normal heartbeats admits a representation  $\mathbf{x} \in \mathbb{R}^n$  such that  $\mathbf{s} \approx D\mathbf{x}$  and  $\mathbf{x}$  is sparse, namely it has only few nonzero coefficients. This modeling assumption corresponds to learning a union of low dimensional subspaces of  $\mathbb{R}^p$  where normal heartbeats live. To detect [Carrera *et al.*, 2016] whether a heartbeat  $\mathbf{s}$  is anomalous or not we solve the *sparse coding* problem

$$\mathbf{x} = \arg \min_{\tilde{\mathbf{x}}} \|\mathbf{s} - D\tilde{\mathbf{x}}\|_2, \quad \text{such that } \|\tilde{\mathbf{x}}\|_0 \leq \kappa, \quad (1)$$

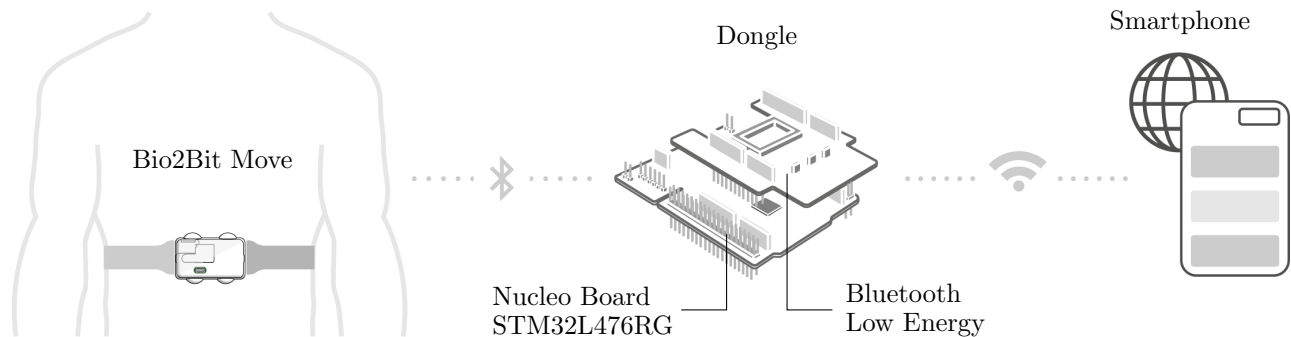


Figure 1: The user wears Bio2Bit Move (on a chest strap) and the dongle (in a bracelet, or hanged on a belt), which communicate over a Bluetooth connection. The *training phase* requires a few minutes of ECG signals acquired in resting conditions, which the dongle segments into heartbeats. These represent the training set that is sent to the user’s smartphone, where the dictionary  $D_u$  and the threshold  $\gamma_u$  are learned. These are sent back to the dongle together with adapted versions by built-in user-independent transformations. During *online monitoring*, the dongle receives the ECG signal from by the Bio2Bit Move, segments each heartbeats and estimates the heart rate. For each heartbeat, it performs the sparse coding w.r.t. the dictionary that matches the current heart rate. Finally the dongle computes the reconstruction error, and raises an alert when it is above the selected threshold.

where  $\|\cdot\|_0$  denotes the number of nonzero coefficients. This problem is NP-Hard and has to be addressed by greedy algorithms, such as Orthogonal Matching Pursuit (OMP) [Pati *et al.*, 1993]. We use the reconstruction error  $e(\mathbf{s}) = \|\mathbf{s} - D\mathbf{x}\|_2$  to assess the conformance of  $\mathbf{s}$  to  $D_u$ , thus  $\mathbf{s}$  is detected as anomalous when  $e(\mathbf{s}) > \gamma_u$ . The threshold  $\gamma_u$  is the minimum distance of anomalies to the learned subspaces of  $\mathbb{R}^p$  containing normal heartbeats. It controls the amount of false positives and is estimated during configuration.

To allow online execution on the dongle, we designed a highly optimized variant of the OMP [Carrera *et al.*, 2017], meant for undercomplete dictionaries (having  $n < p$ ), which are the most effective at modeling heartbeats. Our anomaly-detection algorithm achieves excellent performance on the benchmark dataset MIT-BIH [Moody and Mark, 2001] and on ECG signals acquired using the Bio2Bit Move [Carrera *et al.*, 2016].

**Domain adaptation:** Heartbeats get transformed when the heart-rate increases, and the dictionary  $D_u$  that properly describes heartbeats in resting conditions might not be anymore appropriate for monitoring the user  $u$ . Similarly, a fixed  $\gamma_u$  does not allow to maintain a constant false positive rate. An extended training set including heartbeats at different heart rates would allow learning multiple pairs  $(D_u, \gamma_u)$ . Unfortunately, for safety reasons, training data can be only acquired in resting conditions. Thus, we pursue a transfer-learning approach [Pan and Yang, 2010], and adapt  $D_u$  and  $\gamma_u$  to track heart rate variations.

We learn transformations [Carrera *et al.*, 2017] to adapt both  $D_u$  and  $\gamma_u$  from a large dataset of ECG signals from several users [Jager *et al.*, 2003]. To preserve the structure of subspaces where normal heartbeats lives, we learn a set of linear transformations for adapting dictionaries to different heart rates. Per-

haps surprisingly, our user-independent transformations can successfully adapt user-specific dictionaries and thresholds, even referring to different sensing apparatus. Our dictionary-adaptation algorithm outperforms other transfer-learning solutions [Shekhar *et al.*, 2013], and is compatible with the online execution on the dongle.

### 3 Practical Aspects

The Bio2Bit Move is a prototype having maximum envelope of 55x40x14 mm, even though the final product sizes can be significantly reduced to yield a non-invasive wearable device. Its battery allows to steadily sense and transmit via BLE the ECG signals for up to 20 hours. The dongle has been replaced by a development board NUCLEO-L476RG [ST, 2016] which embeds an ultra-low-power microcontroller unit (MCU) based on the high-performance ARM Cortex-M4 32-bit RISC core, operating at a frequency of 80 MHz. This MCU is a likely reference for low-power dongles. The board is also equipped by a BLE evaluation board (X-NUCLEO-IDB05A1) to communicate with the Bio2Bit Move.

We measured the execution times and the power consumption of the proposed anomaly-detection algorithm, to show that it can be used to perform long term monitoring on the Bio2Bit-Dongle. Our optimized OMP [Carrera *et al.*, 2017] requires on average 1.360 ms to compute the reconstruction error of an heartbeat, which is compatible with human heart rates, and it 48% less than the computing time of a standard OMP implementation. Dictionary adaptation has no overheads, since dictionaries can be pre-transformed during training and stored in memory. The average current absorbed by the dongle during 20 minutes of online monitoring is 10.01 mA. Thus, when the dongle is equipped with a 592 mWh battery such as the one adopted on the Bio2Bit Move, it has 16 hours monitoring autonomy.

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