MobileECG: An Ubiquitous Heart Health Guardian

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Abstract: Electrocardiogram (ECG) is a widespread and efficient medical procedure for monitoring heart health. ECG is a fast, low-cost and non-invasive examination. Its output allows anomaly analysis by health experts. Despite its application in clinical environments, ECG acquisition and analysis as a daily routine is far from being a reality for a large part of the world's population. In this context, we present here a mobile and pervasive platform, named MobileECG, which provides ECG signal acquisition, automatic feature extraction and real-time prediagnosis. Furthermore, MobileECG implements the ubiquitous computing features. Hence, it runs on mobile devices (smartphone or tablet), assuring this way anytime and anywhere access for anyone to its functionalities. MobileECG is in fact an ubiquitous Heart Health Guardian. Besides, MobileECG supports ECG data integration and publication using Linked Data technology, providing a public knowledge base, which may be used to support complex queries, run mining algorithms and yield collaboration among experts.

1 INTRODUCTION

Electrocardiography is a technique used to record electrical potential oscillations produced by cardiac activity. Temporal evolution of such oscillations is called the electrocardiogram (ECG) signal, which is the most widespread test in cardiology for the diagnosis of cardiac diseases and anomalies. The human body by itself acts as a conductor of electrical current, and any two points on the surface can be connected by electrodes to record an ECG or monitor the heart's rhythm. The time-series obtained by the electrocardiographic record contains a series of waveforms and complexes, which are called the P-wave, the QRS complex, and the T-wave, which are separated by regular intervals. The analysis of ECG signal behavior (waveform pattern, duration and interval) allows the extraction of a variety of information, which can subsidize the identification of a great variety of heart diseases.

Chronic non-communicable diseases (NCD), including heart disease and cancer, are responsible for approximately 70% of all deaths worldwide, according to the World Health Organization (Daar et al., 2007). Allied to this fact, the world population is aging. Such a context requires a significant need to monitor patient's health status, while she/he is in her/his personal environment. Consequently, a plethora of wearable systems for health monitoring has been developed and applied for providing real-time feedback information on individual's health condition, either to the user himself, to a medical center, or directly to a health professional.

Over the last decades, ubiquitous computing has gained critical importance for implementing health care applications. Ubiquity provides the means to make health care services available for anyone at anytime and anywhere. Thus, patient data may be acquired by biosensors containing embedded microprocessors, coupled up with bluetooth modules. Furthermore, a mobile application may execute signal processing or data analytic techniques on collected data, or even simply forward collected data to a physician's or a clinic's computers.

In this paper, an innovative pervasive and mobile platform for ECG signal acquisition, processing and prediagnostic extraction is presented. The proposed platform, denoted *MobileECG*, is able to collect and preprocess ECG raw data in a mobile device (smartphone or tablet). Thereafter, prediagnosis algorithms are executed in order to trigger alerting messages to the patient, physician, or emergency station, which should be sent by means of a WiFi or cellular network.

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Besides, *MobileECG* maintains an integrated ECG data repository, which stores an integrated view of ECG data coming from heterogeneous sources (with different ECG data standards) and data of patient, treatment and drug data sources. Such a repository can be used by machine learning algorithms to automatize prediagnosis.

Empirical experiments on real ECG datasets have been conducted to evaluate MobileECG efficiency and effectiveness. The results reveal that MobileECG can be an important tool for helping health experts to identify heart diseases more quickly in a more reliable way.

The paper is structured as follows. Section 2 analyzes approaches similar to the one presented in this paper. Section 3 details the different steps of the proposed platform. In Section 4, results of empirical experiments are presented to highlight the benefits and feasibility of the proposed approach. Finally, section 5 concludes the paper and points out future work.

2 RELATED WORK

A literature review on pervasive health care systems is presented in (Orwat et al., 2008). According to the authors, 60% of investigated systems provide analytical and diagnostic functionality. Only 46% implement automatic alerting, and from this, only 14% support an alerting function generated by a mobile device. Since pervasive health care systems encompass a wide variety of components, one can classify them by the following criteria: ECG data acquisition systems (Venkatachalam et al., 2011), real-time ECG digital signal processing (Madeiro et al., 2012; do Vale Madeiro et al., 2017), feature extraction (Elhaj et al., 2016; Martis et al., 2014), ECG remote monitoring systems (Worringham et al., 2011), collaborative databases (Gonçalves et al., 2011) and machine learning techniques (Luz et al., 2016; Elhaj et al., 2016).

In (da Silva et al., 2015), the authors describe a biosensor for sensing ECG signals, with minimal electrical contact points with users, a so-called off-person ECG. The key goal is to support ECG signal acquisition on palms or fingers. Thus, the proposed biosensor can be embedded in any object with which the user interacts.

In (Wen et al., 2008), the authors propose an ECG telemonitoring system. According to their approach, the Holter Monitor will record the ECG signal of the patient continuously up to 48 h. The monitored data is transmitted to the server through the Internet when a wired network is available. The Holter also contains a software program performing real-time ECG classification. When specific abnormal heartbeats are detected, the Holter transmits them with the GPS (global positioning system) information to the server via MMS (multimedia messaging service) in real-time. The physician at the server side can communicate with the patient also by using MMS. In the server, a GIS (geographic information system) is used for locating the patient in an emergency case by using the GPS information packaged in the MMS message.

In (Worringham et al., 2011), the authors propose a system to enable walking-based cardiac rehabilitation in which the patient's single-lead ECG, heart rate, and GPS-based speed and location are transmitted by a programmed smartphone to a secure server for real-time monitoring by physicians. According to the authors, the feasibility of this approach was evaluated in 134 remotely-monitored exercise assessment and exercise sessions in cardiac patients unable to undertake hospital-based rehabilitation. Completion rates, rates of technical problems, detection of ECG changes, pre- and post-intervention six minute walk test (6 MWT), cardiac depression and Quality of Life (QOL) could be measured. Several exercise and post-exercise ECG changes were detected.

In (Ngo and Veeravalli, 2014), DuyHoa Ngo et al. have proposed a platform based on Web Semantic technologies which provides the storage of features extracted from the ECG signal within a database following *Linked Data* patterns. The authors emphasize that the proposed platform is part of a healthcare system based on cloud data storage, which also captures ECG signals and other vital signs through biosensors located on the surface of the patient's body.

Thus, one can enumerate two important strengths of the proposed platform: the reproducibility of the methodology is notorious due to the fact that the proposed hardware and software are open-source; MobileECG provides basis for integrating multiple ECG data sources, including data from biosensors and data from public or institutional databases which may potentialize the accuraccy of pattern recognition processes.

3 THE MobileECG PLATFORM

The *MobileECG* architecture presents the following components: acquisition module, mobile application module, ECG signal processing and feature extraction module, ECG data extraction module, and finally, the data integration and publishing module. Fig. 1 depicts an abstract model of the proposed architecture, emphasizing the physiological data flow, from the patient to the ECG data repository. For the sake of clarity, the *MobileECG* components are grouped by their behavior in a client-server architecture. Thus, the acquisition and mobile application modules are located in the client area, whereas the other modules are in the server area, as web servers. Each one of the aforementioned components is described in detail and analyzed next.

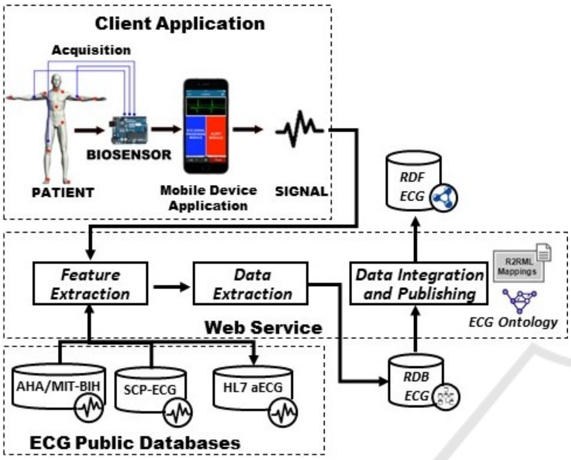

Figure 1: Overview of the MobileECG platform.

3.1 Acquisition Module

The acquisition module is composed of a biosensor coupled with an Arduino microcontroller and it is located in the client area. The capture of the ECG biopotentials is performed by the biosensor, which measures and amplifies electrical potentials derived from the electrical activity of the heart, and then transmits the analog signal to Arduino. An open-source hardware that allows direct communication (SHIELD) with an Arduino microcontroller has been deployed as biosensor. The electrodes used for signal acquisition consist of three leads which should be placed on the wrists and right ankle of the patient. The shield converts the analog differential signal (ECG biopotentials) into a single stream of data as output. A third order “Besselworth” analog filter’s cutoff frequency is set to $f_c = 40$Hz, and the output analog signal is discretized via a dedicated ADC embedded in the Arduino board. Default values for discretizing parameters are: 10-bit ADC with 256 Hz sampling rate.

The Arduino board is responsible for receiving the analog signal and for converting it into a digital signal. Each discretized sample from each lead or channel is split into two bytes, named high byte and low byte, and each byte is stored in packets. Thereafter, each individual byte from the packet is serially transmitted to the bluetooth module, which in turn sends ECG raw data to a mobile device.

3.2 Mobile Device Application Module

The mobile application is in charge of establishing connections with a paired device (bluetooth module associated to a given biosensor and Arduino board) and for searching for unpaired devices. Whenever a device is selected, the mobile application collects the bluetooth identification of the connected device and its Mac address.

As soon as the mobile application receives ECG raw data from a given device, it is able to plot ECG signal buffers on screen as long as a 5-second buffer of ECG signal is completely filled. A 5-second buffer of ECG signal contains 21,760 bytes. The mobile application triggers a thread, named Connection-Thread, which receives the Mac address of the paired device. Within the Connection-Thread, we define a number of bytes (or packet length) transferred from the Arduino bluetooth module to the mobile device on each transfer. Thus, an Android device continuously receives packets of 289 bytes from the Arduino bluetooth module. Each received packet is stored into a byte array (length of $21,760$ bytes). Thereafter, the mobile application triggers the ECG data buffer decoding process. This process searches for each pair of synchronizing bytes (A5 and 5A) and for the pair of bytes corresponding to the ECG sample of a given channel. Since the second channel has been defined as default, high and low bytes are located, respectively, five bytes and six bytes after each pair of synchronizing bytes. Thus, a given ECG sample is computed as the sum of the low byte and high byte shifted by 8 bits left. Each computed ECG sample is stored in a buffer array which will contain a 5-second ECG window for subsequent display on screen and subsequent sending to the Web Service. After filling a 5-second ECG signal buffer, the mobile application forwards the pre-processed ECG buffer to the Web Service. After sending each ECG buffer to the Web Service, the class Plot-Real-Time finally performs the plot of the buffer.

3.3 ECG Signal Processing and ECG Feature Extraction Module

As soon as the mobile app finishes the ECG buffer transmission, the Web Service (Apache Maven) joins all received signal buffers and stores them in a single file. A set of algorithms for digital signal processing is performed, including signal filtering for denoising, wavelet transform (time-frequency analysis) for selective enhancement of the QRS complex, P and T waves, wave peak detection and waveform delineation. The main goal is to extract the following parameters: P-wave amplitude, P-wave duration, PR interval, QRS amplitude, QRS duration, T-wave amplitude, T-wave duration, QT and ST segments, and intervals between beats. Those algorithms have been implemented using Matlab, which is an IDE development environment widely applied for digital signal processing (Islam et al., 2012).

The first stage for ECG feature extraction is responsible for detecting the QRS complex, which is the most expressive waveform of the ECG signal regarding amplitude and period of oscillation. The correct detection of the QRS complex and its precise delineation are fundamental conditions for efficient detection and segmentation of the other waves. Additionally, it provides the necessary support for algorithms able to recognize patterns of cardiac arrhythmias. After proceeding with the denoising process, a sequence of filtering routines are established for enhancing the QRS complex and attenuating artifacts and other physiologic waves. The Wavelet Transform, the First-Derivative function, and the Hilbert Transform are sequentially computed, and the module of the resultant analytic signal is used at a decision stage. An adaptive threshold algorithm is applied over the resultant filtered signal for individual detection of each QRS (Madeiro et al., 2012). Then, the computation of an indicator related to the area covered by the QRS complex provides the detection of QRS onset and offset (Madeiro et al., 2012).

Concerning P-wave and T-wave detection and segmentation, firstly, we apply Wavelet Transform over signal windows established between segmented QRS complexes for estimating T-wave and P-wave peak locations. Then, we fit the parameters of a synthetic function, computed as a composition of two Gaussian functions, in order to model each waveform (T-wave and P-wave) by evaluating the normalized root mean square (RMS) error. This approach provides the delineation of each waveform (by detecting onsets and ends) and the computing of parameters related to the wave width and to a distortion factor of the Gaussian functions which also characterize their morphologies (do Vale Madeiro et al., 2017). All the above explained algorithms, built as Matlab language scripts, are compiled and converted in a single executable file. After the Web Service receives all the ECG signal buffers and converts them into a single file, the Web Service itself calls a Java method that runs the referred executable file. Then, the set of all ECG extracted parameters (waveform peaks and widths, segments and intervals) are converted into text files. After obtaining these text files, the Web Service calls a Java method responsible for storing the extracted parameters within a relational database.

As an illustrative example, Fig. 2 presents a set of results showing ECG beat cycles with all the characteristic waves properly segmented, and two time series of the extracted parameters intervals between beats and QRS widths.

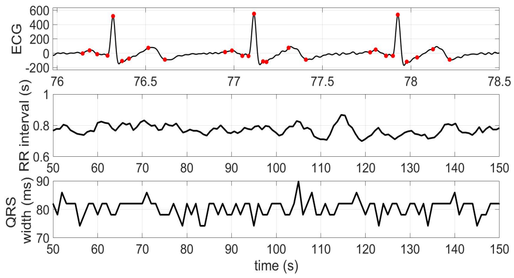

Figure 2: Practical example of ECG feature extraction by applying algorithms over the signal sent by Android app.

3.4 Data Extraction Module

This module consists of storing features extracted from an ECG signal in a relational database. By doing this, it is possible to formulate SQL queries in order to relate ECG signals to properties of a given diagnosis. Figure 3 brings the schema of the proposed database. The ECG table contains an identification of a given ECG record (exam) and also some clinic/diagnosis information from the corresponding patient, such as his/her systolic and diastolic pressure at the time of ECG acquisition. The table Patient contains some identification data of a given patient, such as document number, birth date and birth place. The Prescription table stores information on current medicines taken by a given patient. Drug is fed with medicines related to treatments for the most common cardiac diseases. The table Cycle relates the PQRST complex to a unique cardiac beat. Tables related to P-wave, QRS complex and T-wave contain the identifier of the cycle to which they belong. Moreover, they contain information derived directly from the process for waveform detection and segmentation: onsets, offsets and the corresponding amplitudes.

Tables $Cycle_{D}iagnosis$, $ECG_{D}iagnosis$ and $ECG_{C}ardiopathy$ provides to associate ECG waveform patterns to known cardiac conditions and/or cardiac diseases, such as: conduction disorders, arrhythmias, cardiomyopathies, and other events. The content of such tables may result from Machine Learning algorithms, or may derive from ECG public databases, in the case of ECG signals originated from those databases, or even may derive from manual specialists' annotations.

3.5 Data Integration and Publishing

Advances in heart disease research have been hampered in part by the fragmented gathering and storing of data. Among the major ECG standards, we can highlight: (i) AHA/MIT-BIH (Physionet) (Goldberger et al., 2000a), an ECG data format extensively used in cardiac physiology research; (ii) SCP-ECG (Mandellos et al., 2010), which is an ECG European standard that specifies a data format and a transmission protocol for ECG records; and (iii) HL7 aECG (Bond et al., 2011), which is an ECG data American standard adopted by the Food and Drug Administration (FDA), from the USA, for clinical research.

This knowledge needs to be integrated. To make matters worse, typically heart disease knowledge is expressed in ambiguous terminology. Without the aid of a well-defined knowledge representation, the ad hoc data integration is hard work. In addition, another fundamental challenge to heart research is querying complex heart data.

In this context, we propose the designing of an integrated repository of ECG data whose purpose is: (i) to integrate data in heterogeneous ECG standards, that is, to store ECG data coming from various sources with different data standards (AHA/MIT-BIH, SCP-ECG and HL7 aECG); (ii) to integrate data about cardiac diseases, cardiomyopathies, treatments and drugs with LOD[1] (Linked Open Data); (iii) to store ECG data coming from Patient's smartphones; (iv) To make possible the querying of complex heart data; and (v) to enable running data mining algorithms over integrated data.

Therefore, to support the design of the integrated ECG repository, we propose the use of Semantic Web technologies, such as: RDF, OWL, SKOS and SPARQL. These technologies enable the explicit representation of knowledge and its processing to deduce new information. Besides, they provide an environment where heterogeneous data can be combined based on a common knowledge representation, the schemata can be extended in an easily and dynamic way, and applications can query that integrated data and draw inferences using vocabularies.

In (Gonçalves et al., 2011), the authors proposed an ECG reference ontology, that is, an ontology resulting from an application-independent representation of the ECG domain. This reference ontology can be used to support the design of interoperable versions of ECG data formats like AHA/MIT-BIH, SCP-ECG, and HL7 aECG.

This ECG reference ontology can be used to support the redesign and the possible unification of existing ECG data standards. In this sense, it can be used to support the design of an interoperable and collaborative ECG data repository, which can store ECG signals from various data sources with different ECG data standards. However, in order to build a wide ECG repository that makes it possible to answer complex queries, it is necessary to extend the reference ontology proposed in (Gonçalves et al., 2011), adding concepts related to drugs, treatments, and disease causes, among others, which is one of the goals of the MobileECG platform. In this way, we use the vocabularies *ecg* [2], available in the work (Gonçalves et al., 2007), and *health* [3] (additional terms).

The *ecgo* vocabulary, contains terms created by the proposed approach. Fig. 4 presents the ontology applied in this step. As we can observe, it contains proposed classes for providing inference and classifying of cardiac rhythms (e.g. $ecgo : SlowRhythm$, $ecgo : NormalRhythm$, $ecgo : FastRhythm$), types of cardiac beats/cycles (e.g. $ecgo : NormalBeat$ and $ecgo : JunctionalEscapeBeat$) and possible ECG diagnosis (e.g. $ecgo : PersistentAtrialFibrillation$ and $ecgo : LongQTSyndrome$).

The mappings between the relational database schema and the extended ontology have been executed by means of the R2RML language and the D2RQ tool (Priyatna et al., 2014). It is important to emphasize that it is not necessary to use an ontology to perform mappings with the D2RQ tool; however its use greatly facilitates the mapping process.

The MobileECG platform allows you to import ECG signals from any repository using one of the following standards: AHA/MIT-BIH, SCP-ECG and HL7 aECG. To support this import process, we have implemented a wrapper for each one of these three formats. Thus, to import a particular ECG signal, from a public database, it is necessary to follow three steps: (i) initially, download the files containing the signal, from a public database; (ii) then, apply the set of algorithms described in the Section 3.3 for extracting the features of the signal; (iii) finally, the data of the signal must be extracted, similar to the process described in the Section 3.4.

The data integration and publishing module consists of a Web Service which uses Java methods for accessing the relational database containing the information extracted from the ECG signals and exports the relational data to the RDF format. We split the process into two steps. In the first step, we create a dump of the relational data in RDF format. To perform this step, we use the D2RQ tool together with the mappings in the R2ML3 language, which associates

[1] https://lod-cloud.net/

[2] http://nemo.inf.ufes.br/biomedicine/ecg.html

[3] Available at https://health-lifesci.schema.org

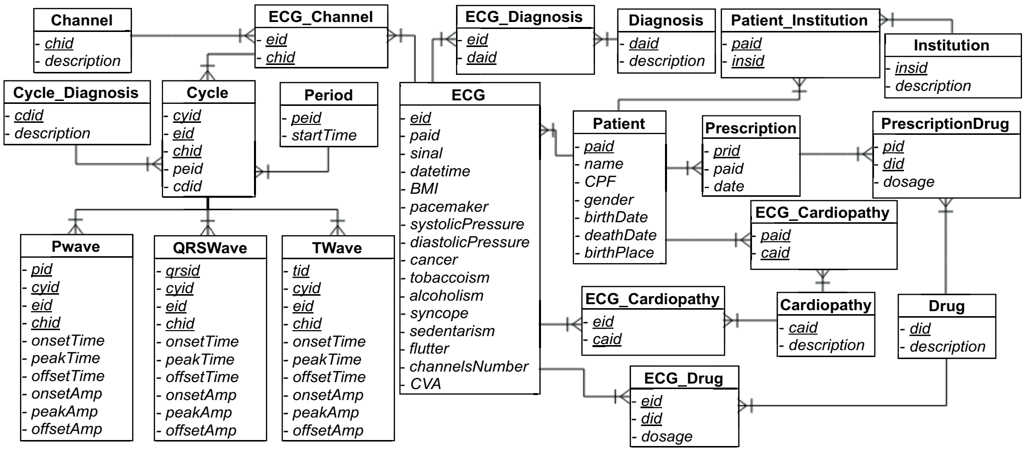

Figure 3: The relational database schema.

the relational database schema with the ontology vocabulary adopted to represent the ECG signals. In the second step, the RDF data present in the dump generated previously are materialized in an RDF triplestore, more specifically in Virtuoso, in a semiautomatic way. Virtuoso provides a SPARQL endpoint that is provided to perform semantic queries.

The RDF Repository is a collaborative database for heart research. It makes possible the identification of data cohorts (including patients, medicines, treatments, and ECGs) for study, and the export of data for statistical analysis. Besides, the RDF Repository will make it possible to infer new knowledge through the use of machine learning algorithms.

4 EMPIRICAL EVALUATION

In order to assess the potentials of the proposed approach, empirical evaluation have been carried out. Firstly, we evaluate the performance of the Arduino code for ECG signal acquisition, conditioning and for sending ECG data to the bluetooth module.

In terms of memory consumption, using Olimex SHIELD-EKG-EMG for analog signal acquisition, Arduino Uno and IDE Arduino 1.8.5, we obtain that sketch (code) uses 2272 bytes (7%) of program storage space and global variables use 223 bytes (10%) of dynamic memory, leaving 1825 bytes for local variables. Regarding the mobile application, we conduct the experiments using smartphone model LG-M250ds and Android version 7.0. We have measured the smartphone memory comsumption, immediately before and immediately after the smartphone application starts to run. We can observe a significant increasing for memory consumption while the class Plot-Real-Time performs the plot of the 5s-ECG signal buffer.

According to Fig. 5, the total use of memory is 37.99 MB immediately before the first ECG signal buffer is exhibited on the mobile screen, increasing to 56.07 MB (see Fig. 6) while the ECG signal buffer is being plotted, during 5 seconds, and again decreasing to 37.99 MB.

As already mentioned, after the mobile app concludes the ECG buffer transmission, the Web Service joins all the received signal buffers and converts them in a single file. We have measured the average time required for specific ECG signal processing tasks which runs in the Web Service, in terms of the total duration of a given record. Thus, for those experiments, we have used a 2.70 GHz Intel(R) Core(TM) i7-7500U CPU, 8 GB of RAM and Windows 10 Home, version 1803, for running Web Service. We have obtained the results illustrated in Table 1.

Table 1: Performance evaluation (processing time) for extracting ECG signal features within Web Service (percentage of the signal duration).

ECG Signal processing task	Processing time
ECG signal filtering for denoising	0.129%
QRS complex detection and delineation	15.43%
T-wave and P-wave detection and delineation	26.638%

Querying over ECG signal data is a rather complex task, since the data is stored in unstructured binary files. On the other hand, the MobileECG platform enables the execution of semantic queries. To demonstrate this fact, we present a query which was executed on an RDF database generated through the MobileECG approach.

Sparql Query 01: Which male patients over 60

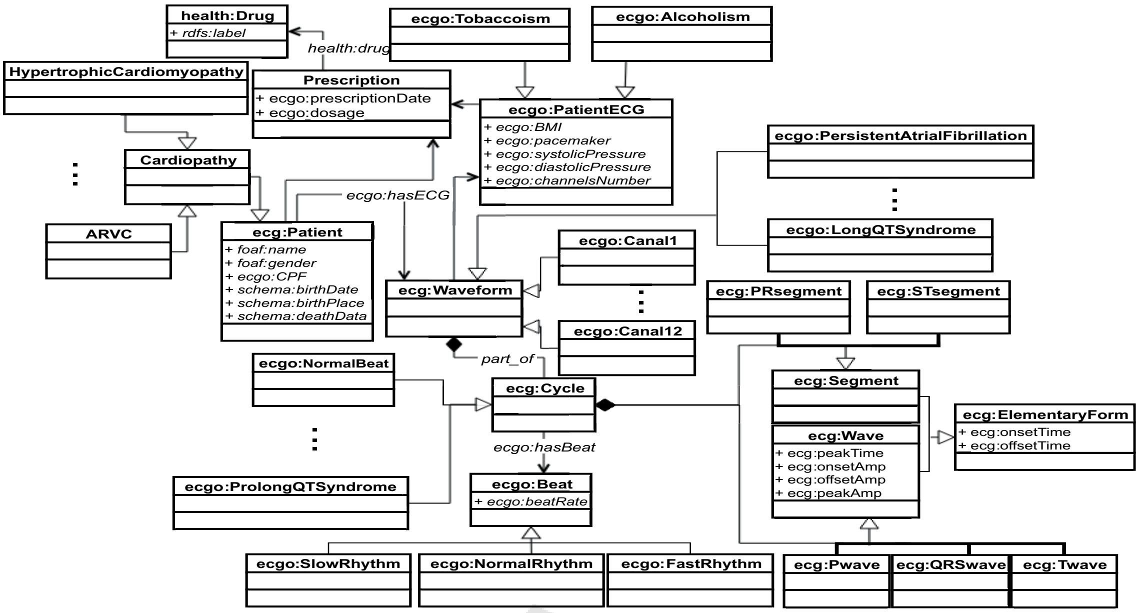

Figure 4: Scheme of the ontology applied in the data integration and publishing module.

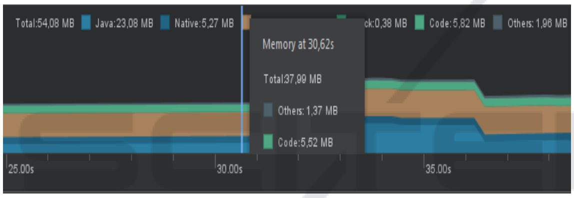

Figure 5: Memory consumption immediately before the first ECG signal buffer is exhibited on mobile screen.

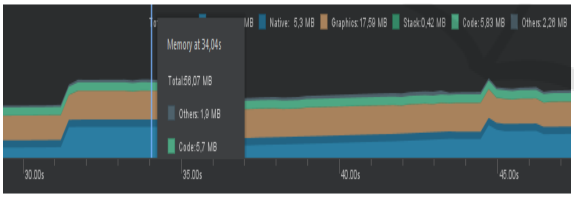

Figure 6: Memory consumption immediately after the first ECG signal buffer starts to be exhibited on mobile screen.

years old have had accelerated beats (over 100 beats per minute) within the ECG?

```
SELECT ?patient
WHERE {?patient a health:Patient ;
     health:age ?age ;
      health:gerner ?gender ;
      ecga:hasECG ?ecg .
      ?ciclo ecgo:part_of ?ecg .
      ?ciclo ecgo:hasBeat ?bat .
      ?bat a ecgo:FastBeat.
FILTER(?age >60 && ?gender = "male")}
```

Figure 7: Sparql Query 01.

Finally, we have computed the number of generated RDF triples as we increase the number of full-processed ECG records, e.g. ECG signals for which we have published the corresponding data in the RDF repository. For this experiment, we have considered applying 30-min ECG records from MIT-BIH Arrhythmia Database (Goldberger et al., 2000b) at the following scenarios: 1, 5, 10, 20, 30, 40, 46 full-processed ECG signals. The obtained results are illustrated in Fig. 8, evidencing a linear increase in the number of RDF triples, and, therefore, in the use of memory as we increase the number of full-processed ECG signals (RDF repository).

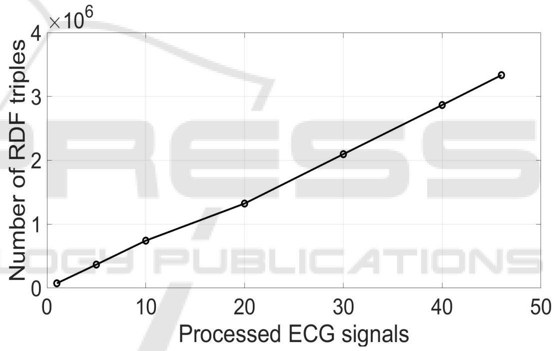

Figure 8: Amount of generated RDF triples per number of full-processed ECG records.

5 CONCLUSION

In this work, we introduced MobileECG, a complete cardiac activity monitoring and prediagnosis solution. The platform comprises everything from the stage of signal acquisition, through biosensors, Analog/Digital conversion through the Arduino, digital signal transmission executed by a mobile application, to the stage of ECG feature and data extraction, integrating and publishing, through Web Service technology. Additionally, a collaborative database is maintained to integrate and store ECG data coming from heterogeneous sources and data on patients, treatments, and drugs. The database is published using Linked Data standards. A case study was analyzed aiming at to demonstrate MobileECG properties. As future work, anonymizing patient data techniques should be implemented, aiming at the protection of individual information. Moreover, machine learning algorithms will be deployed for classification/recognition of arrhythmia and other events.

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