E-safe: Smart Ecg-based Authentication On-wrist Healthcare Wearable System

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***Abstract*—E-SAFE, an IoT-based multimodal health monitoring system, offers a low-cost wrist-based gadget designed especially for the elderly facing the high risk of falling. This paper introduced an affordable solution to securely monitor the elderly health vitals, particularly in the current Covid-19 pandemic. The suggested system integrates a biometric ECG-based authentication process, allowing users to safely access a mobile health monitoring application in real-time. This on-wrist system is a proof-of-concept realized on the Arduino platform to monitor vital health parameters, namely temperature, ECG (electrocardiogram), oxygen saturation (SPO2), heart rate and falls. The obtained experimental results conducted on human subjects carrying out different daily activities show good ECG-based user identification accuracy of 94% using the SVM model and efficient fall-detection using only an accelerometer.**

***Index Terms*—ECG-based authentication, IoT, healthcare, wearable system, machine learning, power consumption.**

I. Introduction

THE elderly population is growing around the world at a dramatic pace, leading to an increase in the population dependency rate. In fact, according to the United Nations Department of Economic and Social Affairs study, the number of elderly people (60 years old or more) should reach 21% of the world population by 2050. Each year, approximately 30% of elderly people are victims of falls. Thus, the prevention from such falls has become an important issue and providing healthcare monitoring solutions is of paramount importance [1] especially with the current context of Covid-19 pandemic. In addition, the progressive developments in biosensors and wireless technology mainly in the industry 4.0 and the IoT (Internet of Things) era, have accelerated the development of small interconnected devices with different functionalities and performances in particular in the healthcare sector [2]. These have provided the sector with what is called Wireless Health Monitoring Systems [3]. Indeed, the need for self-health monitoring and preventive medicine is on the increase, and this is where wearable devices are more and more trustworthy. Consequently, the industrial wearable market size has evolved drastically and will grow from $3.79 billion in 2019 to about $8.40 billion by 2027 [4]. Nowadays, many mobile smartphone-based devices on are becoming more and more common. They are eventually the center of the mobile computing and communication systems in our daily lives. Therefore, monitoring via a mobile phone has become a modern requirement for everyone.

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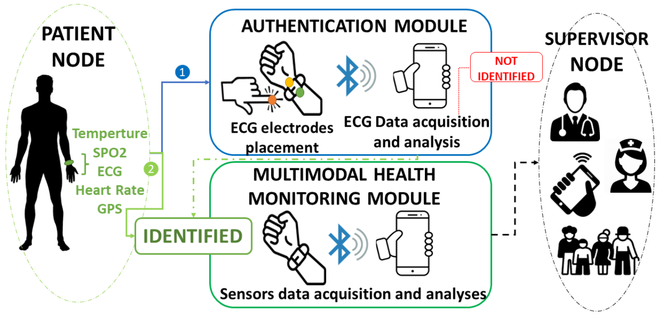

Fig. 1. Design overview of the proposed wearable healthcare device

The main goal of this paper was to describe an industrial low-cost and secure wearable healthcare monitoring system called E-SAFE (Elderly SAFEty). This system is based on new emerging technologies such as biometric authentication, machine learning, IoT, wireless communication, cloud data analytic, and embedded low-power architecture. The wearable device allows the collection and evaluation of different body vital signs as well as their continuous long-term monitoring. It also enables the elderly to alert relatives or caregivers via instantaneous notifications independently of the location of the patient in case of anomaly or fall detection. To this end, an Android-based mobile application was developed. The proposed device has been successfully deployed and fully tested proving its efficiency in health monitoring.

The remaining of this paper is structured as follows: Section 2 described the proposed E-SAFE device and detailed its different parts. Section 3 illustrated the experimental setup and introduced the obtained evaluation results in terms of efficiency and power consumption. Section 4 discussed and compared these results to those of the state-of-the-art systems. Section 5 concluded the paper with suggested an outlook on some future perspectives.

II. E-SAFE: Proposed secure healthcare device

In general, an IoT system architecture consists of four principal layers: i) Sensing Layer; ii) Networking Layer; iii) Processing layer, and iv) Application layer. Figure 1 provides an overview of the proposed IoT based multi-modal healthcare architecture where two major steps were specified, i.e, patient authentication and health monitoring. First, to enable his/her authentication, the patient has to wear the wristband including two ECG electrodes and place the index of his right hand on the third electrode. Once identified via the mobile application, the band will acquire data through several sensors in order to ensure a multi-modal health monitoring including fall detection. When the band is removed, the mobile application will logout automatically. An authentication will then be required for further use. Such a biometric authentication ensures both data privacy and security.

A. ECG-based authentication module

Biometrics, particularly based on dynamic ECG signals, is one of the most effective and secure means of authentication [5], [6]. Its ease of use has resulted in its rapid adoption in many fields. In fact, the global market for biometric technology is expected to reach $59.31 billion by 2025 [7]. The proposed system applies a biometric authentication technique based on ECG signals. More precisely, for the first time use, the user has to position his fingers on a specific capture sensor to record his instantaneous signal. Then, a pre-processing phase is performed. Several descriptors are extracted in order to verify the user's identity and confirm the uniqueness of the captured signal. These descriptors are provided for a Machine Learning (ML) classification model, which allows identifying a correlation between the signals of the concerned person, thereby allowing his authentication. Figure 2 illustrates the implemented system. The ECG sensor is connected to the wearable device that sends the acquired signal to the authentication mobile application via Bluetooth protocol. It also communicates with the cloud to store the captured real-time data. At this stage, the input signal is filtered. In fact, the ECG signal denoising is required to obtain a robust recognition model. Then, the descriptors are extracted before an ML-based algorithm is executed where the classification model takes the set of extracted features as input. The whole process can be detailed as follows.

1) Pre-processing: In all electronic devices, immunity against noise is an essential characteristic, in particular for the very sensitive ECG signals. Thus, denoising is mandatory to obtain a robust recognition model. Power-line interference and Baseline Wander are the main factors of noise in the ECG signal. Thus, to solve this problem, we used a second order bandpass Butterworth filter with 2Hz and 40Hz cut-off frequencies [8] followed by a smoothing filter.

2) Features extraction: To characterize the unique signature of each person, the QRS complex in the ECG signal need to be detected. In fact, it is the most recognizable and unique part of an ECG signal, as it reflects the electrical activity of the heart during the ventricular contraction. Referring to state-of-the-art, the extraction is based on the Pan-Tompkins algorithm since it is the most widely used QRS complex detector showing good detection results [9], as well as its good performance in handling noisy ECG signals [10].

Once the R peak locations are detected, the fiducial features P, Q, S and T through a time-domain method should be extracted [11]. The R-R interval is calculated with Equation 1, where *fs* is the sample frequency and *Rloc* is the temporal location of the R peak.

$$Rloc(n+1) - Rloc(n)/fs(sec) \tag{1}$$

To identify the P-wave, a time window is created with bounds ranging from 65% to 95% of the R-R interval. The P-wave represents the signal maximum value in this window. It is identified through choosing the minimum value of the signal in a time interval starting 20ms before the corresponding R-peak. The S-wave is the minimum value of the signal in an interval starting after the corresponding R-peak. To identify the T peak, a time window is created with bounds ranging from 15% to 55% of the R-R interval. A set of 51 descriptors are extracted based on different signal waves, while considering the candidate R peak as the origin.

TABLE I
EXPLORATION OF THREE ML CLASSIFICATION MODELS FOR ECG-BASED AUTHENTICATION

	SVM	KNN	Decision Trees
Accuracy	0.94	0.88	0.62
Learning Time (seconds)	0.01	1.03	72.03
Size of the model (Ko)	110.1	128.6	128.6

3) Evaluation: In order to assess the efficiency and accuracy of the authentication solution, the following parameters were evaluated:

- Adaptive threshold: During the analysis of the signal amplitude, the algorithm uses two thresholds (THR(SIG) and THR(NOISE)) which are continuously adapted to the ECG signal quality.
- Search for undetected QRS complexes: According to the previous step, if the amplitude of the detected R peak is below the THR(SIG) threshold, the peak cannot be considered as a QRS complex. However, if there is no real peak detected in a sufficient time, the algorithm assumes that a QRS peak is neglected, which triggers a "searchback".
- Elimination of insignificant peaks: It is impossible for two QRS peaks to occur in a duration less than 200ms. This is a physiological constraint, which corresponds to the depolarization of the ventricles.

The algorithm, implemented in Python, was firstly evaluated using an open-source ECG-ID database [12], which contains 310 ECG recordings of 90 individuals. Each signal lasts about 10 seconds and has 10 R peaks (10 heartbeats).

4) Classification model: The used ML classification model is based on the SVM (Support Vector Machine) using the Radial Basis Function (RBF) kernel. In fact, the SVM has shown good performance compared to K-nearest neighbor and Decision Trees classification algorithms as shown in Table I. The used data-set was split into 74% and 26% used as training and testing data-sets, respectively. The obtained model accuracy was 94%.

To design a single-user system, the model needs to be specifically trained for the user's ECG signal in order to allow his unique authentication and ensure the system security. Moreover, the authentication is required whenever the user wears his bracelet in order to activate the multi-modal health monitoring module described in the following subsection.

B. Multi-modal health monitoring

This module is responsible of acquiring vital health signs via the integrated sensors and performing the health status control and monitoring. It is mainly based on three layers as described in the following.

1) Sensing Layer: Different heterogeneous sensors (digital, analog, serial) are connected to the processing platform; they collect the required raw data and then convert them to useful information. In fact, apart from the ECG signal, the other vital health parameters are acquired from their corresponding sensors namely: body temperature, SPO2 and acceleration, with a sampling rate of 100 Hz. Table II summarizes the integrated sensors. The normal health status of the user is identified based on the ranges of the measured data sensors. These ranges can be modified, according to the medical staff suggestions, depending on the user's parameters such as age, gender, etc.

2) Networking Layer: This layer is responsible for efficiently transmitting data to corresponding processing units. There are several communication protocols used for healthcare devices such as ZigBee, Bluetooth, Wifi and Lora. In this work, the used sensors were connected to a processing board, which sends the collected data to a Bluetooth Low Energy (BLE)-enabled peripheral data aggregation mobile device, since the BLE represents a reliable and easy solution for signal transmission [13]. Then, a smartphone or a tablet will be the networking gateway that will gather the acquired sensor data and transmit them to a data processing IoT cloud.

3) Data processing Layer: This layer is responsible for processing and analyzing data in order to retrieve valuable knowledge from the acquired sensor data. In fact, the collected data will be sent in real-time by the mobile application to the cloud where a fast processing is performed to compare each physiological parameter (temperature, BPM and SPO2) to a defined threshold in order to detect anomalies. For the acquired data from the accelerometer, a classification model will be applied to analyze and predict results. In fact, to facilitate the integration of the data in the model, we used the Dictionary Learning (DL) approach [14]. Indeed, the most significant features are extracted from the acquired data to identify health problems through a prediction algorithm.

To detect falls from daily activities, we used the dataset described in [15]. During the learning phase, the activities considered as ADL (Activities of Daily Living) are: walking, sitting, standing, clapping, opening and closing a door, moving an object, and tying shoes. Whereas, the fall activities are: fall forward, fall backward and fall to the side. The data-set contains 792 samples: half of them simulate ADL activities and the remaining are falls, split into 75% data for training and 25% data for testing. For the data analysis, a 5-second sliding window was used to guarantee the efficiency and accuracy of the fall detection. In this step, we explored three DL classification algorithms, namely: Sparse Representation-based classification (SRC), DL for separating the particularity and the commonality (COPAR) and Fisher discrimination DL (FDDL), in terms of accuracy, sensitivity and specificity as shown in Table III. According to the obtained results, the most efficient algorithm was the FDDL, which was used in this research work.

4) Application Layer: After analysis, and once a fall event is detected, an alert message will be sent to relatives or caregivers. In addition, notifications are transmitted when hazardous situations are detected. Indeed, once pathological abnormality is detected, an alarm notification will be triggered and sent to the contact person. Furthermore, authorized users can continuously monitor the patient's real-time health condition as well as his location, from anywhere at any time, via the developed mobile monitoring application. Figure 2 highlights the whole process.

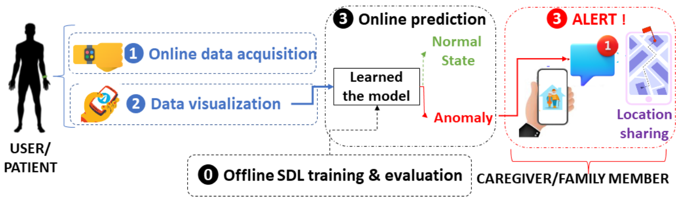

Fig. 2. The implemented E-SAFE process

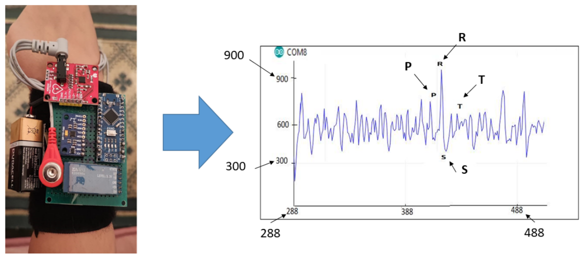

Fig. 3. Real-Time Patient's ECG data visualization

III. Experimental Set-up

The presented system was implemented using a low cost and low power board, Arduino Nano, as shown in Figure 3. The ECG signal was captured through an ECG sensor (AD8232 [16]), 3 electrodes and connection wires. Other sensors were also integrated: body temperature (LM35 Analog Temperature Sensor), accelerometer (ADXL 345 sensor configured with 100 Hz for sampling rate and 4g scale) and MAX30100 Pulse Oximeter Sensor. The voltage supply of these sensors is equal to 3.3V. A BLE sensor (HM-10) was used to transmit the collected data to a mobile application. The Arduino processing platform performs data acquisition, pre-processing and controls whether measured vital health signs are in normal or abnormal range. The different vital-sign readings can be visualized using serial plotter, which is an Arduino IDE tool. Figure 3 shows an example of the acquired ECG signal through the AD8232 sensor.

A. ECG-based authentication

In this subpart, real ECG signals of 10 elderly people were recorded at different time periods while carrying out different activities. A data file with the descriptors of each real signal was configured. From each input signal, 4 QRS complexes were detected. The signals were pre-processed and the corresponding descriptors were extracted. Testing real data using our the SVM classification model yielded an accuracy rate of 97%. A mobile application was developed to allow the authentication process. In fact, once the person is recognized based on his ECG signal, he can access the application; otherwise, access will be denied as the person's identity does not exist in the classification database. Figure 4 presents some interfaces of the E-SAFE mobile application.

B. Fall detection

Fall detection is extremely important for the elderly health monitoring. To study the efficiency of using only the accelerometer sensor to detect falls, we have conducted different evaluation experiments based on the FDDL algorithm while modifying the used sensors (accelerometer, gyroscope

TABLE II
INTEGRATED SENSORS IN THE WEARABLE HEALTHCARE DEVICE

	Description	Readings	Observation
ECG AD8232	Captures the electrical activity of the heart & Measures the heart beat rate (BPM)	PR and QT intervals	allows user (patient) authentication normal case if BPM values in the range [60,100]
MAX30100	Measures Oxygen levels in the blood	SaO2 varying from 0 to 100%	normal case if values in the range [95,100]
Body Temperature LM35	Measures the body temperature in Celsius (degrees)	Temperature value	The average normal temperature is 37°C. Sends alerts when 38°C<temp<36°C.
ADXL 345	Measures acceleration on three axes: X, Y and Z	3 Gravity accelerations	Detects fall or ADL

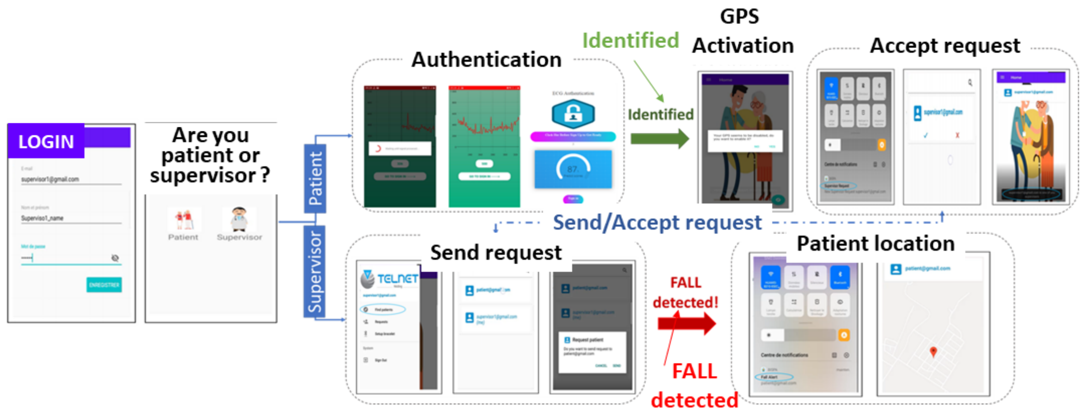

Fig. 4. The developed mobile application

TABLE III
EXPLORATION OF THREE DL-BASED CLASSIFICATION ALGORITHMS FOR FALL DETECTION

	Accuracy	Sensitivity	Specificity
COPAR	98.19 %	99.87 %	99.22 %
FDDL	98.76 %	99.89 %	99.79 %
SRC	97.96 %	99.56 %	99.38 %

TABLE IV
FALL DETECTION-BASED SENSOR SELECTION

Used sensors	Accuracy	Sensitivity	Specificity
Accelerometer + Gyroscope + Magnetometer	96.35 %	92.71 %	100 %
Accelerometer + Gyroscope	97.64 %	94.79 %	100 %
Accelerometer	98.75 %	96.82 %	100 %

and magnetometer) as shown in Table IV. The tested configurations were evaluated in terms of accuracy, sensitivity and specificity. These metrics present the overall true detection, the ability to detect true falls among all the detected potential ones and the capacity to detect real ADL in all the detected ones. In our study, Table IV proves that it would be enough to use just the accelerometer to have an efficient and reliable device. When a fall is detected, E-SAFE sends an alert while indicating the user's location, as shown in Figure 4.

C. Evaluation

In this research work, our implemented wearable device was also evaluated in terms of power consumption, as displayed in V. To lower the power consumption, the ATmega328P processor is active during all the performed tasks and put in an idle mode when the BLE sensor operates. Seemly, when there is no data transmission via Bluetooth, the HM-10 is put in a sleep mode, thereby reducing its

TABLE V
POWER CONSUMPTION OF THE DEVICE COMPONENTS

Component	Current Supply	Power consumption
Arduino Microcontroller (Atmega328P)	(Active) 9 mA (Idle) 1.75 mA	45 mW 8.75 mW
ADXL345	23 µA	75 µW
AD8232	170 µA	561 µW
LM35	60 µA	198 µW
MAX30100	0.7 µA	2 µW
HM-10 BLE module	(Active) 10 mA (Sleep) 1.5 mA	34 mW 4.95 mW

activity. The power consumption of the wearable device was estimated taking into account the fact that the measurements were carried out each 60 seconds. This was ensured via triggering interruptions to activate the sensors every 1 minute.

Table VII shows the power consumption as well as the execution time of the different tasks performed by the device: data measurement via sensors, data processing by the microcontroller (MCU) and data transmission through the BLE module. The MCU remains in idle state for roughly 56 seconds. The average power consumption during a given period T was estimated using Equation 2.

$$P_{av} = \frac{(E_{proc.} + E_{meas.} + E_{trans.} + E_{idle})}{T} \quad (2)$$

Where $E_{proc.}$, $E_{meas.}$, $E_{trans.}$ and E_{idle} are the consumed energy by the data processing, data measurement, data transmission and inactivity states, respectively. Accordingly, the average power consumption of our proposed wearable E-SAFE device is approximately 11.6 mW. If a 900 mAH battery were used, the system autonomy would be up to two days (45 hours) approximately. Figure 5 shows the battery life time of our optimized system compared to a normal run. It is to be noted that an important part of the power

TABLE VI
COMPARISON OVERVIEW

Reference	Included Sensors	Processing platform	Comm. protocol	Security access	Mobile/Web App	Power
WISE [17]	Heart beat, body Temperature, blood pressure sensors	Arduino	Wifi	No	Yes	N.A
[18]	AD8232 ECG sensor	STM32F103RC	Wifi	No	Yes	N.A
[19]	Accelerometer, Heart rate and body Temperature	NodeMCU ESP8266 Dev. kit	Wifi	No	ThingSpeak	N.A
Our work	Accelerometer, Pulse Oximeter, body Temperature, ECG	Arduino Nano	BLE	ECG-based Authentication	Yes	11.6 mW

TABLE VII
EVALUATION METRICS OF THE PERFORMED TASKS

Task	Time Duration (sec)	Consumed Power (mW)
Data measurements	30	0.83
Data processing	4	45
BLE transmission	0.006	34

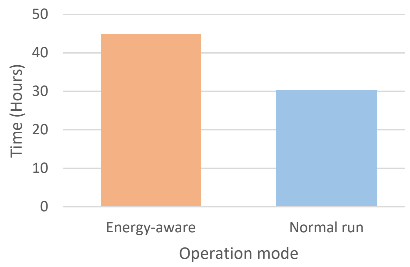

Fig. 5. Autonomy estimation

is consumed by the MCU as well as the communication module. Thus, further works need to be carried out to further optimize the power consumption and enhance the system autonomy. Meanwhile, the current prototype consumes less power and proves its efficiency in particular for elderly who spend most of their time sleeping. As presented in Table VI, the comparison between our proposed system and the other state-of-the-art wearable devices confirms the effectiveness of our E-SAFE gadget.

IV. CONCLUSION

In this paper, an E-SAFE gadget, a low power and low cost wearable device, was proposed for health monitoring. The device allows the user authentication via his ECG identification, ensuring the security of the system. The suggested E-SAFE also integrates an accurate fall detection approach making it a good option for many people, particularly the elderly. As a proof of concept, the whole system was implemented based on Arduino Nano board that uses an ATmega328P microcontroller while integrating the needed health sensors and the required BLE module. A mobile application was also developed to allow the user as well as authorized people to monitor potential health issues. The main objective of the proposed system was successfully achieved. Our future work will focus on further analyzing the ECG data to detect/identify potential heart diseases. Another perspective is to design a smart data filtering approach in order to rapidly and efficiently retrieve the most valuable information from the sensor data.

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