Multi-sensing of fragile persons for risk situation detection: devices, methods, challenges

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***Abstract*—The ageing of the world population and the major technological advances made in recent years have naturally resulted in the development of technical solutions for measuring physical conditions and assisting elderly and/or fragile population at their homes. Physiological, motor and even environmental measurements are excellent indicators of their health status. Furthermore, connected wearable technologies in the framework of Internet of Things allow for risk situations prevention for this kind of population. Recent advances of Artificial Intelligence techniques make possible real-time mining of multi-sensory data and decision making with high accuracy. Nevertheless, to train models and to perform online real-time detection of risk events from heterogeneous taxonomy robust wearable devices have to be designed. In this paper, we review existing solutions for human sensing for these purposes and present the implementation of a multi-sensor device for the recognition of risk situations with a focus on the data synchronization.**

***Index Terms*—Recognition of risk situations, Data synchronization, Multi-sensors data analysis, Artificial Intelligence.**

I. Introduction

The world population continues to age significantly. In France, a statistical study carried out by the French national institute of statistic and economic studies (INSEE) shows that nearly one in three people will be over 60 years old in 2050, compared to 21.5 % in 2007 [1] . As a result of this demographic change, new models of ageing in which technology plays a role are emerging. Furthermore, frailty not always related to the ageing, but can result from chronic diseases, post-surgery periods. Services on the basis of IoT technologies allow surveillance of quality of life of such kind of population by continuous monitoring, detection or even prediction of adverse events such as falls, stress situations, major oversights. Thus, ageing in the best possible conditions and maintaining frail subjects at home has become a major challenge, almost a necessity.

The scientific community was interested very early in the issue of population ageing and the solutions that could be proposed to support this transformation in a healthy way [2]. In addition, industrial actors have identified a growing market for this applications and they are now proposing a variety of basic solutions. Smartphones and smart devices are very popular, and more cheap than medical specialised devices. With these IoT devices, it is possible to collect different vital signals, such as heart rate, body temperature, blood pressure, or still identify if the user has undergone an accident, such as fall. Many projects are then carried out in the world [3], with architectures including objects connected with different types of sensors (physiological, contextual, ambient...) and different detection techniques.

The aim of these studies is to slow down the process of frailty of elderly or not and propose support systems when frailty occurs to enable subject to remain as independent as possible. To illustrate our comments, we can give the definition of the frailty of the elderly as it is most often presented in the scientific literature. Frailty is a geriatric syndrome characterised by weakness, weight loss and low physical activity associated with adverse health effects [4]. Frailty manifests itself in an (age-related) biological vulnerability to stressors and a decrease in physiological reserves, which limits the ability to maintain homeostasis. The validated and widely used five-point fragility criteria for screening are: self-reported exhaustion, slowed performance (by walking speed), weakness (by grip strength), involuntary weight loss (10 lbs. in the past year) and low physical activity are the composite results of multiple organ systems.

The objective of this research consists in proposing a wearable sensing device to prevent risk situations for fragile people in their homes. We stress, that the challenge consists in instrumenting only the subject and not the environment.

In the reminder of the paper we analyse existing solutions for human sensing with wearables and describe our proposed device for detecting and monitoring risk situations at home. Section II is a review of existing research. In section IV, we introduce architecture of our system of detection of risks situations. Section V presents data acquisition and pre-processing. synchronization is presented in section VI. Conclusion and future work are drawn in section VII.

II. Wearable devices for subjects sensing and risk situations detection.

A. Human sensing with wearables

The attempts to objectively monitor the condition of fragile subjects in ecological environments, that is at their home or in every-day life have become quite popular [4]. The proliferation of wearables specifically in wireless connection framework made possible collecting of a huge amount of physiological, motor and environmental data to evaluate condition and risks. The fundamental work synthesising these concepts and practices was published by Ramesh Jain [5] introducing the concept of ”Objective self”. Here an instrumented fragile person e.g. suffering from a chronic disease could assess his/her condition and elaborate a daily strategy of behaviour assisted by automatic analysis of multi-sensory data. This concept was further developed and florished to the the general interest multimedia community expresses towards healthcare applications.

In the field of assistance to vulnerable people, there are two types of interest. The evaluation of risk situations after the fact, the purpose of which is to evaluate the state of health of the person and risk environment [2], and studies aimed at detecting risk situations in real time and therefore preventing them.

B. Risk situations

Several studies have been conducted to define the most common risk situations encountered by fragile people [6]. According to these studies, the most common accidents among the elderly are falls. It is the third damage after heart attacks and cancers [7]. Nevertheless, the risks faced by older adults differ accordingly to their individual medical history. Except the cases mentioned above, there are other more specific situations such as Parkinson’s patients or people with Alzheimer’s disease in addition to diabetics, people with heart failure or respiratory failure and other chronic diseases. The situations of these patients differ according to the disease. For example, for Parkinson’s patients the most urgent risk are Parkinson’s falls, which are very common, for Alzheimer’s patients they are stress situations, loss of orientation and loss of path. For diabetics they are hyperglycemia and hypoglycemia. Considering the many studies on risk situations for fragile people we have chosen to design a heterogeneous system that can be used in many situations of frailty. Thus, if a generic device should be designed with a coverage of heterogeneous cohorts of fail subjects, it should detect as many risk situations as possible.

Without referring to a specific pathology the risk situation as defined by psychological studies [8] are:

- Risk of falling: resuming accidental falls, they are widely studied and today we can determine with an accuracy ranging from 200 to 600 ms the fall onset, which is by definition the element that precedes the fall;
- Risk of loss of orientation in space: very frequent situations in patients with dementia [9], but it also concerns fragile people. We often talk about loss of landmarks in a known place.
- Risk of major forgets: they include forgetting to close the door, forgetting to turn off the stove, forget to take one’s medication and loss of orientation;
- Risk of domestic accidents:.
- Risk of abuse: attempted fraud or attempted intrusion by a third party;

Analysing the proposed taxonomy, it is clear that the different risk situations are not equivalent in semantic charge. Hence falls and fall onsets can be detected from such a simple analysis of accelerometer signal as thresholding of magnitude [10]. The risk of loss of orientation in space can also be detected by the analysis of signals from GPS (outdoor situation) and magnetometer. These are very ”popular” risk situations well studied in the state-of-the-art. The second category of risks: risk of major forgets, of domestic accidents, of abuse require much more rich data, including visual information to record at subject’s home to detect them. Furthermore, these semantic situations make a real challenge: will it be possible to recognise these risks using only wearable devices? In the following section we will discuss different risk scenarios and corresponding sensors.

C. Risk detectors

In order to detect risk situations and ensure a good quality of life for frail subjects, it is useful to have continuous access to their physiological, motor and environmental information. Physiological information reflects the individual’s state of health as well as emotional state, while motor information helps identifying his position and warning the individual if the current state is dangerous (fall, loss of orientation). Finally, the ambient information can be used to alert about major omissions and risks of domestic accidents [11]. The main and most studied group of approaches for risk detection without considering specific pathologies such as e.g. diabetes is the fall and fall onset detection. It is performed with contextual measures.

D. Contextual measures

In most fall detection studies, the same approach is used. It is based on monitoring the motor activity of the subjects using one or more sensors [12]. Studies can be classified into two main categories: those using wearable technology (accelerometers and/or gyroscopes) and those using non-wearable technology (fixed cameras or Kinect sensors).

Motor measures are essential for the detection of accidental falls. The most commonly used in fall detection are acceleration [13], angular velocity and magnetic field [14].

Coming back to the Taxonomy of our risk situations, it is obvious, that highly semantic items require classical multimedia sensors: video and audio. Wearable sensors of this kind have been used for such studies as Lifelog data collection [15], early detection of Alzheimer’s disease [16]. Hence it is promising to use them in a risk detection problem for both i) a posteriori analysis and ii) real-time risk detection.

E. Multisensors Data fusion

Multi-sensor data fusion is a well-established field of research, there exists a vast literature on the subject [17]. Any measuring system, connected objects based on a single sensor, or on several sensors considered individually, suffers from several limitations, such as:

- Failure of one of the sensors that can lead to a loss of measurement;
- Presence of noise due to the pass-band drop in transmission....

- Non-determinism of biological subjects.

The use of data from multiple sources ensures greater reliability of the device, increased robustness to environmental interference and improved measurement accuracy.

F. Choosing the location of the sensors

a) Sensor location for motor data acquisition: Placement of dynamic sensors depends on the target detection task. Motor information varies according to the different parts of the human body during movement. Hence wrist-placed accelerometers allow for fine classification of instrumental activities of daily living when combined with ego-visual information [18] For fall onset detection, the authors of [12] ,report that the arm, wrist, hip and leg are not the appropriate positions to recover motor information for this, due to the high frequency and complexity of movement, although these are often more comfortable placements for the subjects. The most appropriate region to distinguish falls from other movements with motor information is located at the solar plexus. The latter undergoes the subject's global movements, it is not disturbed by the movements of the rest of the body.

b) Location of sensors for physiological data acquisition: The physiological data required to detect the risk situations from taxonomy for frail subjects are essentially body temperature, electro-dermal response (EDA) and heart rate.

According to numerous studies [19], the optimal place to take measurements of electro-dermal activity is the palm or fingers of one hand for the high concentration of eccrine glands responsible for sweat secretions from the human body. However, comparative measurements of EDA taken on the wrist and fingers at the same time [20], prove that the error between the two results is tolerable. Placing electrodes on fingers or palms requires external connections which would make the device cumbersome and very sensitive to movement and/or pressure artefacts.

For conditions of non-intrusiveness, compatibility with the ecological situations in which the device will be worn and taking into account the scientific publications on the accuracy of physiological measurements [21], we have opted for a multi-sensor solution connected to the wrist.

III. Our contribution

In this section we discuss the configuration of sensors for detecting of various risk situations from proposed taxonomy.

In *fall* risk detector, we focus on the analysis of motor sensors signals: such as accelerometers and gyroscope. Here the approach with accelerometer from [22] gives satisfaction. In risk of *loss of orientation in space* we consider two scenarios: i) the subject is at his home, and ii) the subject is outside his home. In the former case, magnetometer change of signal alone can show the lack of orientation of a subject loitering around [23]. In the outdoor environment we pose the landmarks of safety in GPS coordinates, and the risk situation is detected each time the person is out of the marked area.

For more "semantic" risk situations discussed in Subsection II-B which are risk of major forgets, risk of domestic accidents and risk of abuse, no literature is available at present. Of course, the technologies that will be used will employ the winner AI models such as Deep Neural Networks, but they have never been applied to our context.

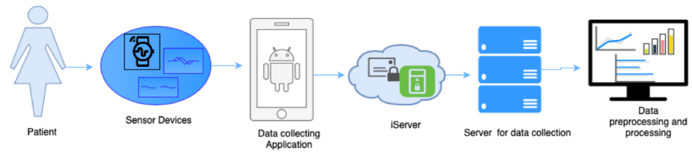

Fig. 1. System Architecture.

IV. System architecture

In this section, we present our system for recognizing risk situations for fragile people. Knowing that it is a multi-modal device, any data is significant by its complementary value with regard to other data.

Figure IV gives an overview of the architecture of the wearable data measurement system. It is composed of a set of connected objects carried on different parts of the body. As shown in Figure 1, it is a four-layer architecture with the IoT layer consisting of a smartwatch, an IoT device collecting motor activity data and a video camera. The second layer is the smartphone, which represents one of the two intermediate layers that runs the application, which allows data to be collected and synchronized before being sent to servers. The third layer is used as an intermediate server as well as for data prefixing and finally we have the last layer that will store the data for the learning phases. In many IoT applications, it is essential that data can be stored locally to preserve confidentiality and is located close to the application that processes and analyses the data in real time. However, the storage and computing capacities of the smartphone are limited and it is therefore necessary to periodically delete the detected data or transfer the sensor data (with the user's consent) to a secure server continuously for long-term archiving. The innermost layer serves as a robust computing platform that includes multiple services, including a web server to host applications that can visualise aggregated sensor data, a sensor database to archive and visualise the detected data from the consenting user's IoT system.

Proposed architecture allows data to be transmitted to our servers in complete security. As illustrated in Figure IV using Bluetooth low energy (BLE) technology, the data collected from sensors and concentrated on Android smartphones is transferred to the servers by gateways for Android smartphones. The smartphone gateway is the application developed. The information collected and stored on the smartphone is transferred to our servers through the middleware iserver. The data is anonymized. The servers are fulfilling pre-processing and analysis of them.

V. Data Acquisition

The multi-sensor data recording scenario includes the recording of motion sensor data, GPS as well as physiological sensor data throughout the day. For video and audio data,

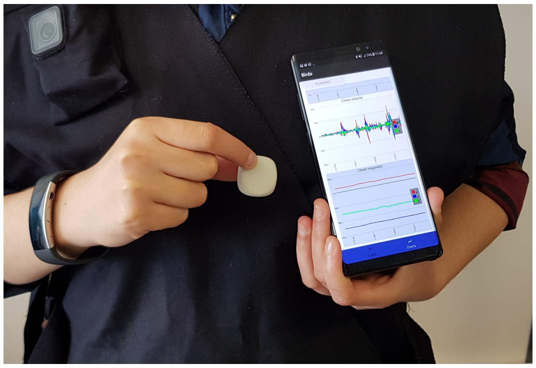

Fig. 2. Wearable connected device

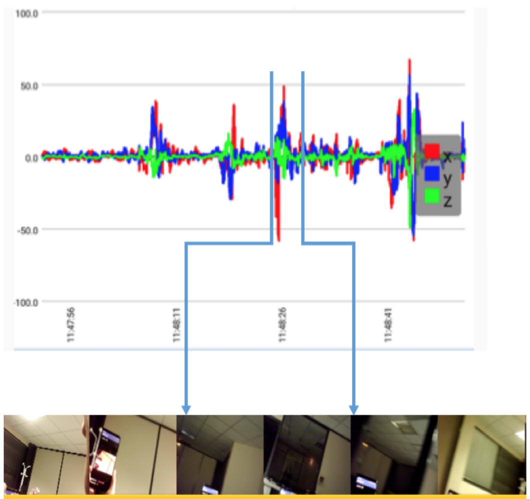

Fig. 3. Camera triggering when detecting risk events on other signals

a continuous recording is not necessary. Indeed, these data allows for context analysis of a risk situation, furthermore, video recording even with data compression generates a huge volume of data. Hence we propose a triggered recording. If an alarm or augmentation of motor activity is declared at any time by processing physiological and motor data, a video sequence is recorded over a defined time interval the length of which is a hyper-parameter of the system, figure V illustrates this activation of the video.

This recording can be seen as performed with a sliding window over time.

The purpose of this scenario is to allow the acquisition of an important corpus in terms of ecological situations, especially distress situations, while keeping a reasonable consumption in terms of battery and storage memory. The device has been designed so that its user can wear it without any discomfort and so that it is as unobtrusive as possible. Figure V gives an overview of the first prototype of the proposed connected solution.

VI. DATA SYNCHRONIZATION

synchronization of hybrid data is a fundamental step before any data fusion. The challenge is all important as the merger is scheduled in real time. This requires scalable clock synchronization as it must provide a common time reference for all data received from sensors.

Since the sensors are designed for long-term operation, to conserve the limited energy of the batteries, most of the connected objects are programmed to go into standby mode in the event of prolonged inactivity. Maintaining a common time reference is important for the moment of restarting the sensors.

The two most important (and conflicting) requirements for such a synchronization protocol are high synchronization accuracy and low power consumption.

To describe the synchronization problem, we will go through four points.

Random transmission delay according to [24], this is the most important source of error to consider. When the available time stamp is that of the MAC layer (as is the case with our data from namely Microsoft Band 2), the synchronization accuracy is mainly affected by interruption and quantising delays. These delays can lead to system desynchronization, and therefore distort our analysis results. Another source of inaccuracy is the fluctuation of the clock frequency. Knowing that the relative drift is not constant, additional synchronization errors are introduced.

Bluetooth Low Energy connection interruption: like any system with radio transmission technology (BLE in our case), connection interruptions occurs between one or more of the connected objects and the smartphone on which the measured data is concentrated. This means that when the devices are reconnected, one or more signals are out of sync.

Signal transmission start As the signals come from different sensors and sometimes from different connected objects, its difficult for all sensors to start transmitting at the same time. If this problem is not corrected, it can cause data desynchronization throughout the data acquisition period.

Material constraints our system uses a battery with a limited charge and sometimes sensors with a quality that deteriorates over time. These material limitations result in desynchronization of our system.

A. Our model of desynchronization

In this section, we model the time stamping errors of multi-sensor data as well as the desynchronization of the sensors between them inspired by [25]. The equation modelling the time stamp recorded on the smartphone as a function of the reference timestamp, the phase shift between sensors, errors due to random transmission delays and the difference in sampling frequency between the two signals is shown below:

$$c_i(t) = h_i(\tau) * x(t) + \theta_i(t) + \phi_i(t) \tag{1}$$

Here $c_i(t)$ is the time stamp observed at the smartphone output, $h_i(\tau)$ is the frequency offset i-th sensor, $x(t)$ is the

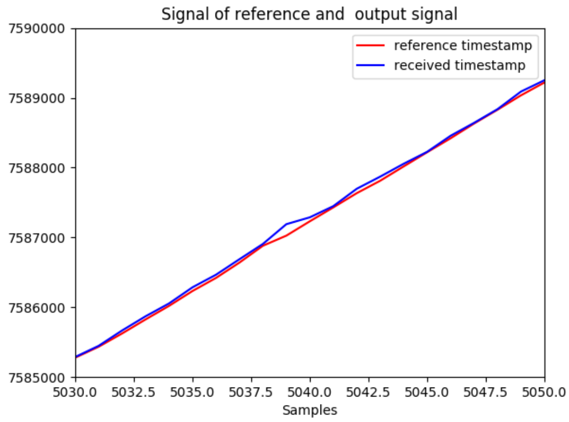

Fig. 4. Timestamps signals of sent (Red) and received (Blue) data

true time stamp, $\theta_i(t)$ is the mistiming of a sensor due to the transmission delay, $\phi_i(t)$ is the phase shift due to the random switching of a sensor. In the case of an ideal time stamp $c_i(t) = x(t)$ with $\phi_i(t) = 0$, $\theta_i(t) = 0$ and $h_i(\tau) = 1$.

The model described in the equation (1) takes into account the non-linear nature of sensor desynchronization. With the BLE protocol, transmission delays are much shorter than in previous Bluetooth protocols, data is less sensitive to interference [25]. Therefore, we assumed $\theta_i(t) = 0$, the model represented in the equation (1), becomes:

$$c_i(t) = h_i(\tau) * x(t) + \phi_i(t) \tag{2}$$

Considering $\phi_i(t)$ to follow Gaussian distribution, we can formulate this problem like least mean square minimisation with regard to parameters h. The figure VI-A illustrates the desynchronization between the moment of sending data and the time of data reception of the EDA sensor.

The model from (2) will be used in our synchronization algorithm we present in the next section.

B. Synchronization algorithms

Several solutions exist in the literature for multi-sensor synchronization. In particular, time stamp correction methods can be distinguished by estimating sending delays and estimation methods at the time of receipt of phase shifts and frequency differences between sensors.

1) Synchronization by time stamp exchange : Three approaches for delay correction models on time stamps for wireless networks are identified: transmitter-receiver synchronization [26], receiver-receiver synchronization [27] and one-way message broadcasting [28] (receiver only). These methods have several advantages, including very low calculation costs, elimination of sending delays and estimation of phase shifts between sensors.

However, these methods are not applicable for our device because our sensors are closed-form and we cannot work on their MAC layers. To do this, the non-deterministic delays due to delays in sending, receiving and accessing the measure were initially ignored.

2) Synchronization of timestamps by frequency and phase estimation: Below, we will mention some methods known in the literature for estimating frequency offsets F_i and temporal phase shift $\phi_i(t)$ between sensors:

The method proposed by [29] only estimates the phase shift between sensors, this makes the approach impractical for a good synchronization of the sensors.

[30], proposes a maximum likelihood estimator, which estimates the communication delay separately, and uses it to estimate the phase shift and frequency offset between.

[30], also proposes a low complexity least squares estimator that eliminates phase shift and frequency offset between signals as well as synchronization delays. [31], proposes a least squares-per-pair approach to estimate the model parameters of each sensor. The low complexity of the least squares-in-pairs estimator seems interesting but it is impossible to apply to our sensors because of the nature of our devices that are closed-form.

C. Proposed solution

The syschronization we propose consists of two steps:

- Eliminating starting phase shift. Different sensors have there own time shifts from the moment they are switched on and the moment they start transmitting data. We use a buffer that only starts capturing data when all the sensors have started transmitting data. For the set of sensors in our device, the buffer should be about $0.6 * 10^5$
- Synchronization of timestamps from different sensors. To do this, we propose to correct, in real time, the time stamp values received by the smartphone by comparing them with the time stamp values generated by the sensor

Considering two signals a real timestamp $c_i(t)$ corresponding to the time at which the data from each i-th sensor is captured and a timestamp signal by the smartphone $x(t)$. We are looking for the best finite impulse response filter to find the desired signal. For this purpose, the error between both is minimized, in the sense of mean square error. Its expression is given below:

$$J(h) = E((c_i(t) - h_i(\tau)x(t)))^2) \tag{3}$$

with $c_i(t) = h(\tau)x(t)$ and E - expectation operator, h - filter response and $x(t)$ is the data of time stamp.

The minimisation method we apply is gradient descent. The algorithm of gradient has the equation:

$$h_{n+1} = h_n - \mu \nabla J(h_n) \tag{4}$$

with n - iteration number. We use the stochastic version of the gradient descent changing with the iterations the packet of data along the time [32].

D. Results of synchronization

According to our experiences on a set of 1000 samples of couples of time stamps from the concentrator smartphone and EDA sensor, the filter converges in case of a very simple configuration: its length is of 1. On the recorded dataset of timestamps, the mean squared error between two signals

$h(\tau) * x(t)$ and $y(t)$ decreases from 236 ms to 142 ms. This is compatible with physiological measures - the fall onset time accordingly to literature [33] is between 150 and 600ms.

VII. Conclusion

This study reported on the design and development of a multimodal system for monitoring fragile people. Based on psychological studies we have elaborated risk situation taxonomy and recording scenario. The system architecture has been described as well as its main modules. The key concept presented in this work is the multimodal approach, which require a propoer synchronization of sensor data. Hence a generic synchronization model was proposed that can evolve with other devices. As part of future work, data analysis will be examined, and deep learning architectures implemented to meet the challenge of multimodal data fusion for the recognition of risk situations.

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