A Review On The Main Algorithms For Measuring Steps, Sleep And Falling In Wearable Applications

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***Abstract*—As the life expectancy is getting bigger worldwide and people begin taking more care of their health, wearables are becoming popular as a health and quality of life device. With this in mind, this paper evaluates methods of step detection, sleep detection and fall detection in wearables, then concludes with showing the best methods among those considered.The study was done by reviewing about 30 articles, some of which were discarded because they did not fit the proposal of the paper. We had as a result a discussion about the error rates of the algorithms discussed in this paper, which highlighted the WPD, for step counter, the Sadeh, for sleep monitoring and the between the junction of the cell phone and the wearable, for fall detection. The review done here allows us to conclude that, with the improvement of technologies and load capacity of the devices, the detection of such actions can become more accurate, while algorithms that use multiple sensors can be improved.**

***Index Terms*—wearable devices, body sensors, sleep detector, steep detector, fall detector, algorithms for measuring, quality of life, error rate.**

I. Introduction

In recent years, people in world have begun to take more care of their health and quality of life, starting to exercise, improve their diet, take care of their physical and mental health, and sleep. Thus, as technology has advanced, devices have emerged to help people with these tasks, and among them are wearable, like smartwatches. These wearable and devices that stay on the wrist are on the rise these days, because, with the improvement of technology, these devices are able to assist in everyday activities, such as showing the time, serving as a GPS, audio player, and also step detection, monitor sleep and detect falls. These last three functions will be treated in this review paper.

The step detection is an essential tool present in many wearable applications, the number of steps a person takes in a certain amount of time is an important parameter for various analyses used in health monitoring present in many different types of devices, for example, with it we can estimate the distance traveled by a person, the amount of calories burned in a certain amount of time, among other factors.

Sleep monitoring, although the devices today do not have an accuracy of the level of exams such as polysomnography, the gold standard exam [1], help to monitor how long we sleep and if we move too much, for example.

The fall detection is a fundamental tool for several people, because it can signal if the user has had an accident, being ideal for cyclists, motorcyclists, and people with difficulty in locomotion, such as the elderly. So, this paper aims to help new researchers, works in progress, or satisfy the curiosity of people who want to better understand the algorithms behind the operation of such devices.

The method used for this research was a literature review, in which we reviewed older articles, such as Sadeh's 1995 [1], to newer ones, such as Brajdic [2]. The research was done by searching for terms such as ”wearable,” ”sleep detector,” ”sleep,” ”quality of life” and ”fallen detector” in sites such as Scielo, Google Academics and IEEE. About 30 articles were read, and those that were referenced here by a criterion of accuracy in their objectives, discussing the data used in an objective manner. Those discarded either lacked relevant information or had the information but did not discuss it succinctly.

This paper was made with the objective of helping future researches in finding a summary of the main technologies and algorithms used in these devices, so that the researcher doesn't spend time reading many other articles and thus speeding up his research.

II. Detection Algorithms

A. Step detector

Currently, there are several ways to detect step using the most varied devices, for wearable applications it is mostly used

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accelerometers associated with the most diverse algorithms due to its portability and use in other health monitoring algorithms. The description and analysis of the main algorithms used, the hidden Markov models (HMM), continuous wavelet transform (CWT) and windowed peak detection (WPD), as well as an alternative that uses the angle variation to determine the step, will be addressed to follow.

HMM – This algorithm uses in its essence statistical models to analyze and determine the step. With the appropriate dataset, in this case the acceleration signal, it can be trained to determine the different phases that are part of the step process and, consequently, indicate its occurrence or not [2].

CWT – This algorithm uses an acceleration signal transform technique in the frequency domain to decompose it into so-called wavelets, which are portions of the signal that carry frequency and time information. From there, all frequency information outside the step frequency band is removed, the inverse transform of the signal is performed, and then the step is determined by the positive crossing of the centred moving average of the magnitude of the acceleration signal [2].

WPD – This algorithm calculates the centred moving average of the magnitude of the acceleration signal, separates it into windows, and based on the peak of the resulting signal, the occurrence of step is determined [2].

Angle variation – This uses to determine the step the variation in angle that the movement of the arms or legs present. It is important to point out that this type of algorithm has a superior performance than accelerometer at higher walking speeds, which have a high associated error rate, as well as it does not require the pre-processing or use of low-pass filter, which are necessary in the other algorithms [2].

B. Sleep monitor

Sleep quality is a factor that influences all human activities, from mental to physical health. A good quality sleep, with a comfortable environment and 8-7 continuous sleep reduces the risk of diseases such as depression, diabetes, depression [3]. So, taking care of sleep is taking care of quality of life. That way, as people realize the importance of it, they start monitoring it, and consequently, companies start making devices to monitor it.

The gold standard for sleep monitoring is Polysomnography (PSG), a laboratory test in which analyzes the patient's brain waves, blood oxygen level, heart rate and body movements are captured, all during a night's sleep [4]. With this examination, doctors can accurately diagnose sleep disorders.

However, it is an expensive and invasive exam because it is necessary that the patient sleeps in the laboratory [4], so we sought cheaper and less invasive methods to measure sleep. One of these methods is actigraphy, done as follows: the patient uses a device that stays in the non-dominant arm, which has acceleration sensors with memory, for at least one week (the doctor should stipulate the maximum time), measuring the patient's movement throughout the period of use, being removed only in the bath [4].

Thus, by means of an application for computer, cell phone or a smartwatch, the sleep can be monitored and analyzed, because the device can register the amount of time awake and sleeping, through the accelerometer of the device, so it can be observed data such as sleep time, whether the patient moved too much or if he woke up at night [4]. This method is inexpensive and non-invasive, and, as much as it has less reliability than PSG it still has a high degree and is therefore adopted by a smartwatch to check sleep [5].

meanwhile, it is worth remembering that smartwatch actigraphy is not efficient for diagnosing users with sleep disorders, because a clinical picture cannot be accurately diagnosed only with wrist movement, and in these cases, PSG is indicated.

There are several sleep-wake algorithms, some public and others are owned by companies, but many are based on Cole-Kripke and Sadeh [5]. The Cole-Kripke algorithm is indicated for adult individuals who have some sleep disorder, as it was developed with data obtained from subjects between 35 and 65 years [6], who half had some sleep disorder, and the other half did not. This algorithm is based on the following formula:

$$\begin{aligned} d = p(&w_{-4}a_{-4} + w_{-3}a_{-3} + w_{-2}a_{-2} + w_{-1}a_{-1} \\ &+ w_0a_0 + w_{+1}a_{+1} + w_{+2}a_{+2}) \end{aligned} \tag{1}$$

Which has its weights calculated for preset times in time intervals, such as 10 seconds, 30 seconds or 1 minute. Being the p a scale factor for the whole equation, the w are the weights for each minute, such that the '-'and '+' stand for the minutes before and after the w zero, which is the specific movement to be measured and a is the average activity obtained by the device. Finally, d is the result, if $d < 1$, indicates that the subject is asleep, and if $d \geq 1$, indicates awake. The best result is obtained when the epoch is equal to 10 seconds, and, through calculations obtained by a set of training and validation, combined with a cross-validation, taken from the subjects tested, we have that the following equation is the most efficient to measure sleep:

$$\begin{aligned} d = 0.00001(&404a_{-4} + 598a_{-3} + 326a_{-2} + 441a_{-1} \\ &+ 1,408a_0 + 508a_{+1} + 350a_{+2}) \end{aligned} \tag{2}$$

Sadeh algorithm is indicated for young individuals, since the study group were young people between 10 and 16 and young adults aged 20 to 25 [1]. It works as follows: With a fixed epoch of 60 seconds in 11-minute window and adapting Webster's method, which was used in the above algorithm, we have formula that changes to each user. The ActiGraph device uses the following formula [7] :

Whereby the Sadeh use one axis (the y), so, the Sleep index are defined as:

$$\begin{aligned} si = 7.601 &- (0.065 * avg) - (1.08 * nats) \\ &- (0.056 * sd) - (0.703 * lg) \end{aligned} \tag{3}$$

Where *avg* represent the average of the activity counts in an 11-epoch windows centered at *t*, *nats* represent the number of epochs in the 11-windows, *sd* represent the standard deviation of counts in a 6-epoch windows, which includes t and the five preceding epochs and lg is the natural logarithm of the activity at epoch t. So, if the $si > -4$, the person is in the sleep state, else, in the awake state.

C. Fall detection

As global life expectancy keeps growing [8] the elderly population are getting more and more fragile in their body configuration, thus monitoring and making sure that they are safe is a problem yet to be solved. On this subject, fall detection systems are being developed to ensure that in the case of a fall, the person receives the needed medical care to lower the injuries.

Fall detection in a wrist wearable is less precise than the other wearable because of the constant movement in Activities of Daily Living (ADLs), so in order to get a more precise detection it is recommended to use a smartphone as a second point of measure. The most used method for fall detection is threshold based. In this paper we will be using three types of threshold formulas: Total vectorial acceleration, Fall index, Absolute vertical acceleration.

Total vectorial acceleration: the module of the sums of acceleration in X, Y and Z axis. Fall index: Sum of the difference in acceleration in each axis, requires a higher sample rate because the samples are compared. Absolute vertical acceleration: calculates the total acceleration in the vertical direction.

Using these measuring methods on the phone is way more accurate than the wrist wearable because of its position relative to the body, with the wrist wearable because of the natural movement of the arm detecting ADLs is more ineffective this way [9].

III. Error Rate

Measurement algorithms have an error rate, which can increase or decrease depending on the measurement method and threshold [2]. Regarding the step detector we realize, therefore, that two algorithms have better performance over the others. If we take the error rate as the main parameter, the detection by angle variation has better performance with an error rate of less than 1% compared to 3% of the other algorithms [10], however, it should be noted that this result was obtained in this specific study, so that other studies may obtain different results. In general, both are efficient and used. Furthermore, this one needs an extra sensor since the accelerometer is indispensable for the calculation of other health parameters and its inclusion is generally already foreseen, which for wearable applications, which always seek the lowest possible weight and size, can be an obstacle. So, in general, algorithms that use accelerometers are the most suitable for the case of wearable, in particular, the WPD has a good performance for these applications with relative simplicity compared to other HMM and CWT that have relatively more complex algorithms in terms of processing.

In relation to the sleep monitor, the algorithm which obtained the best result was the Sadeh algorithm, because it obtained the best Signal Detection Theory d-prime(d', whose value is the difference between the z-score of the false alarm and hit rate), equal to 1.807, and also better sensitivity and specificity. However, one cannot fail to point out that the result of the Cole-Kripke algorithm obtained a similar result, not much lower. This way, we have that both are excellent actigraph meters, however, they are not real time meters, because the data is captured and only after the sleep cycle is fully terminated is the data analyzed, so, the use of these devices inside smartwatches would be of great benefit, because a real time monitoring would help in the search for sleep disorders [11].

Algorithm	Advantages		Disadvantages
HMM	Low error rate	Good performance (Pode deixar em branco isso aqui)	Low computational cost
CWT			
WPD		Good performance with Low computational cost	(Pode deixar em branco isso aqui)
Angle Variation		Good performance at higher walking speeds	Additional hardware (Extra sensor)

Fig. 1. Comparative table of the main step algorithms

Algorithm	Sadeh	Cole-Kripke
Presented the best d'	Yes	No
Best indicated for	Children and Youth	Adults
Advantages	Inexpensive and non-invasive	
Disadvantages	The most used ones do not process in real time yet	

Fig. 2. Comparative table of the main sleep algorithms

On the fall detection subject, if compared to Ifall and Fade the phone and wrist wearable fall detection system gets a 7 and 13 percent increase in accuracy [9] showing that phone and wearable is the most accurate approach to fall detection.

	Advantages:	Disadvantages:
Wriste wearable	Only one devide	Less batery capacity Less processing Power Less precision on detecting normal movement

Fig. 3. Comparative table of the main fall algorithms with only wearable

	Advantages:	Disadvantages
Wriste wearable + smartphone	Greater processing power Larger battery capacity Greater precision on detecting falls because of the position relative to the body	The need for two concurrent devices

Fig. 4. Comparative table of the main fall algorithms with wearable plus smartphone

In general, the algorithms cited are efficient, and this rate varies little from algorithm to algorithm, i.e., in most of the algorithms discussed here, there is not a large difference in efficiency to the point of discarding one to use another, and the device must have an optimization system for each person.

Example: A weareble knows that the user is young or an adult, and thus automatically selects the best sleep detection algorithm, which in this case is Cole-Kripke.

IV. Conclusion

So, as seen in this paper, wearable are on the rise, and with the advancement of technology more accurate will be their findings, assisting in the quality of life of the population.

For the case of step detectors there are currently many algorithms available with error rates very close to zero, it is therefore recommended to choose a simple algorithm with good performance and low computational demand such as WPD. So, regarding the sleep detector, we realize that the method currently used, despite not being totally accurate as the PSG, helps in some issues such as measuring approximately the sleep time and if the user moves a lot, for example. These factors, combined with low cost and low intrusiveness, make wearable to be key devices in the future, while with the emergence of new technologies, more accurate measurements can happen, using real-time data processing, as some more modern devices use the actigraph plus a heart rate monitor [11] . However, such devices are not fully recommended for diagnosing some sleep disorders, since some of these are only verified with PSG [12].

Thus, about fall detection, if possible, is recommended to use the phone as a measuring device for fall detection because of its greater processing power, larger battery and better position relative to the body.

So, to conclude, with a wrist-only monitoring set, people will be able to more closely follow their physical activity, assisting in medical follow-up including.

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