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Evaluation of the Android-Based Fall Detection System with Physiological Data Monitoring

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Abstract— **Aging population is considered to be major problem in modern healthcare. At the same time, fall incidents often occur among elderly and cause serious injuries affecting their independent living.**

This paper proposes a framework which uses mobile phone technology together with physiological data monitoring in order to detect falls. The system carries out collecting, storing and processing of acceleration data with further alarm generating and transferring all the measurements to remote caregiver.

To perform evaluation, an experimental setup involving novice ice-skaters were carried out to obtain realistic fall data and examine the effects of falling on physiological parameters. A fall detection algorithm has been designed therefore to cope with large variations of movement in the torso. The online algorithm operating showed performance results of 90% specificity, 100% sensitivity and 94% accuracy.

I. Introduction

Aging population has been one of the main concerns in most developed countries during the last decade [1]. Most elderly people suffer from wider spectrum of various diseases and more emergency situations such as fall are likely to occur [2]. As a result, they need to be transported to the hospital, observed and provided with medical help if health condition is at risk. However, remote monitoring can help to prevent described scenario, significantly reduce healthcare costs and at the same time maintain patient's independent lifestyle [3].

Fall injury is considered to be one of the most common and dangerous risks among elderly population. The estimated fall incidence for both hospitalized and independently living people over 75 is at least 30% every year. Nearly half of nursing home residents fall each year, with 40% falling more than once [4]. These accidents can have both physical [5] (often head injury) and psychological [6] (fear of falling) effect.

With the recent development on mobile market, smartphones start to play an important role in modern healthcare systems [3]. New features create new opportunities to use smart-phones or tablets for managing and presenting medical data. The list of possible applications has been growing along with market development: early detection of Alzheimer's disease [7], face-to-face communication between doctor and patient[8], complex activity recognition [9] and medicine intake assistance [10]. Modern smart-phones equipped with an accelerometer sensor are also commonly used as fall detection tools [11][12][13][14]. They replace both processing mode and a communication tool while maintaining relatively small size. A choice of processing algorithm depends on final application of the system and varies in different studies. Some of the recent implementation methods apply Gaussian distribution of clustered knowledge [15], neural network [16] and machine learning techniques [17]. However, most of them are initially based on three essential parameters associated with falls: impact, velocity and posture. According to the recent article, combining impact and posture while analyzing the fall case is enough to create a reliable algorithm [18].

In the current research we intend to develop a mobile-based fall detection system with physiological data monitoring. This work is a part of the collaborative project[1] focusing on independent living for elderly people. The main idea is to perform activity monitoring (using phone accelerometer, Figure 1), detect the fall and notify a nursing personnel. For evaluation of the algorithm we asked 7 healthy young people with a minor ice-skating skills to wear fall detection system and perform regular skating activity. Afterwards, we calculate the sensitivity and specificity of the algorithm based on collected data. Moreover, we perform an off-line processing (e.g. danger point and anomaly detection) to demonstrate the possibility of the future correlation analyses between major physiological parameters and fall incident in case of long-term monitoring.

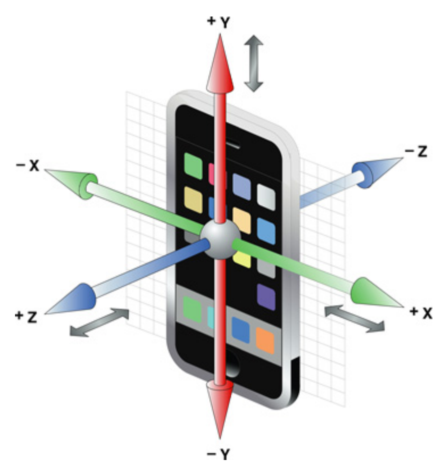

Fig. 1. Smart-phone coordinate axis

In the rest of the paper we discuss some of the recent publications and scientific background within the healthcare

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systems and related areas. It will be followed by the systems design overview and implementation of the proposed ideas.

We finally describe experimental part, demonstrate and discuss current results and propose ideas for a future work.

II. Implementation

A. Fall Detection Algorithm

As it was previously discussed in Introduction, three main parameters are associated with falls: impact, posture and velocity. Combining two of them, however, will provide accurate results and high level of reliability [18]. A fall, including impact, has been defined to have four distinct phases [19]: (1) the pre-fall phase, which is where most normal activity of daily living (ADL) occur, but may contain some instability; (2) the critical phase, when the body experiences a sudden movement toward the ground, ending with a vertical shock; (3) a post-fall phase, when the body comes to rest and the body is lying and (4) a recovery phase. We deploy embedded 3-axis accelerometer sensor and design multi-functional application based on Android operating system. This application will carry out both activity and physiological data monitoring, which means that more than one process will be ran on the phone at the same time. Therefore our goal is to create a simple, but yet sufficient algorithm with a low power consumption rate.

The mobile phone is located on the central part of the waist, corresponding to the body center of gravity. For maintaining acceleration axis, the device is fixed in a special phone case attached to the users belt. The process is split into three main stages. The system starts to receive data from accelerometer and calculate the overall acceleration value (empirically developed activity measure) *Act*:

$$Act = E[|v_a^2 - E[v_a^2]|]; v_a = \sqrt{a_x^2 + a_y^2 + a_z^2}, \qquad (1)$$

where a_x, a_y, a_z correspond to acceleration along 3 axis of the smart-phone coordinate system (see Figure 1). If the impact is registered ($Act \geq$ threshold) during ADL, we consider it as a potential fall risk, pause monitoring process and check orientation of the phone. Using the same acceleration values a_x, a_y, a_z we determine devices' Euler angles with respect to the earth's gravitational attraction:

$$roll = arcsin(\frac{a_x}{gravity}), \qquad (2)$$

$$pitch = arcsin(\frac{a_z}{gravity}). \qquad (3)$$

The very same method is used in games or bubble level applications for smart-phones. A combination of thresholds for roll and pitch angles corresponding to horizontal position of the body triggers an alarm signal informing user about the fall. Before forwarding this message to a smart-home database system or directly to a nursing personnel, user is allowed to cancel an alarm if he/she thinks the fall was false positive and no assistance is required. Otherwise, algorithm complements an alarm with additional data.

The additional data comprises two components. Firstly we deploy accelerometer values occurred during the impact in order to determine falls direction (forward, backward, left-side, right-side). Each direction corresponds to a particular combination of acceleration numbers along the axis (see Figure 2).

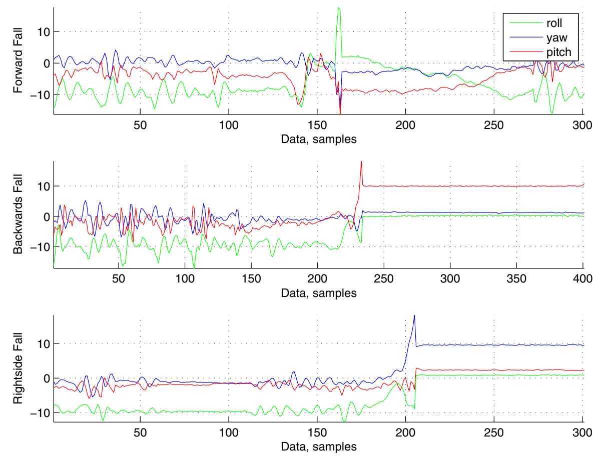

Fig. 2. Roll, Pitch, Yaw variation during different types of falls

We attach a specific value to each direction and include this data in the alarm message. Furthermore, physiological measurements are collected during the monitoring process as a complementary unit. Every time system detects a fall, the last pulse and oxygen saturation value is attached and sent along with the person's location and fall direction number.

After all, data sample consists of alarm index, current geographical location and physiological measurements. Simplicity of presented approach does not affect its sufficiency which was proven in the experimental part of the paper (see Section IV).

III. Experiments and Results

Algorithm evaluation is a primary step preceding stable operating of the system. The most common approach is simulation process when young and healthy volunteers are asked to perform falls multiple times in different directions. Experiments with elderly people would be more relevant, but can obviously lead to an injury and therefore inappropriate.

TABLE I
TEST SUMMARY

					Average	
	TP	**FN**	**FP**	**TN**	**Pulse, BPM**	**SPO_2, %**
Test 1	3	2	0	4	107.1	95.5
Test 2	3	0	0	5	96.3	94.5
Test 3	9	0	0	4	91.1	98.6
Test 4	7	2	0	5	109.4	97
Test 5	7	0	0	5	94.8	96.3
Test 6	7	0	0	5	83.4	93.7
Test 7	9	1	0	5	112.4	93.6
Totall	45	5	0	33		

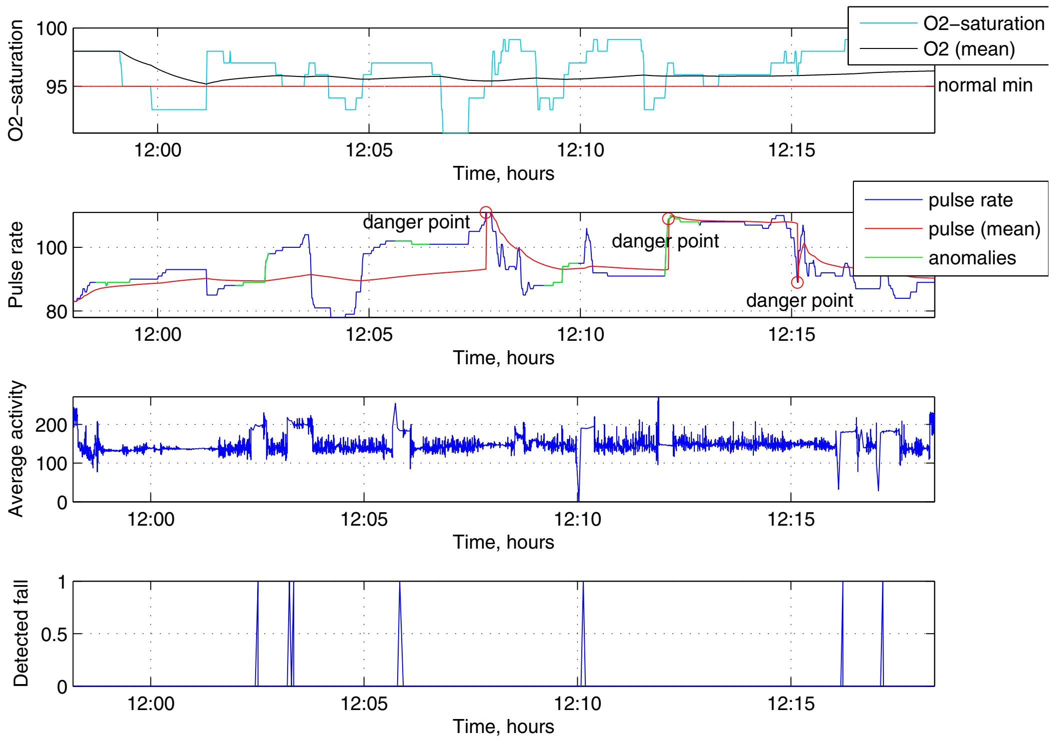

Fig. 3. Monitoring process and fall detection results (Test 5). Contains (1) oxygenation variation, (2) pulse rate variation with processed anomaly and danger point detection, (3) overall acceleration value of the person and (4) registered falls with corresponding time stamps

We found a fair solution which evaluate the system in a real environment and contains both regular movements and fall incidents (see Table I). After a personal consent we ask 7 volunteers with minor winter sport skills to wear mobile fall detection system while performing ice-skating activity. Due to the lack of experience in this area, falls occurred consistently, together with frequent and random motions of the torso. The average duration of the test for each volunteer is 30 minutes. No one was injured or hurt and experimental part finished successfully.

The above proposed approach has a number of benefits. Firstly, we are able to test the system in a situation close to real life when falls appear unintentionally. Secondly, a fair amount of physical activity is involved in ice-skating which can be considered as a stress test to avoid false positive results. Additionally, we perform physiological data monitoring during the experiment collecting heart rate and oxygen saturation measurements. In the off-line mode it is possible to process the data for anomaly patterns[20] and danger points (unexpected variations in pulse signal) depicted in Figure 3. Although it is nearly impossible to build a reliable fall prediction algorithm based on this information, it can give a better insight on the nature of falling behavior and help in the future research. All the volunteers performed from 15 up to 30 min of ice-skating during each session resulted in 50 falls overall. The short and intensive format of the experiment is particularly chosen for evaluation purposes. Long-term monitoring in smart-home environment is planned as a future work within the current project.

Assuming the individual approach during the test, we split data and illustrate personal statistic for each participant including number of falls (1) detected (true positives TP) (2) not detected (false negatives FN) by the algorithm, and number of activity of daily living (3) detected (false positive FP) (4) not detected (true negative TN) as fall events. ADL in our case was represented by various exercises and activities on ice which were not recognized as falls. An extra column displays the average value of pulse/oxygen saturation variation during experimental part. It is important to mention that fall detection procedure was performed in on-line mode during the monitoring process and no post-processing was involved at this stage.

Subsequent evaluation is based on computing sensibility and sensitivity of the algorithm according to the following formulas:

$$Sensitivity = \frac{TP}{TP + FN} * 100\%. \tag{4}$$

and

$$Specificity = \frac{TN}{TN + FP} * 100\%. \tag{5}$$

Out of 50 falls 45 were successfully detected (TP) and only 5 were ignored by the algorithm (FN) which resulted in 90% sensitivity. None of the regular skating activity or exercises were recognized as falls, giving 100% specificity. An extra accuracy parameter

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} * 100\%, \tag{6}$$

corresponding to percentage of true discrimination between falls and ADL resulted in 94%. It shows that it is possible to achieve a high level of reliability for the algorithm combining only two parameters (impact and orientation) when performing the task. Every time a high acceleration value occurred system considered it as a potential fall case and initiated the orientation check.

It is important to mention the difference in acceleration levels between ice-skating and elderly people activity. An idea was to test the system in rough environment with a lot of disturbances and show that it can only react when a real fall occurred. Therefore, it is important to preliminary set the impact threshold to a bigger number to avoid the unnecessary processing. However, the average acceleration lever of elderly is expected to be significantly lower which requires to adjust the threshold accordingly. At the same time, we believe system performance will improve when it comes to distinguishing between falls and regular activities in real life.

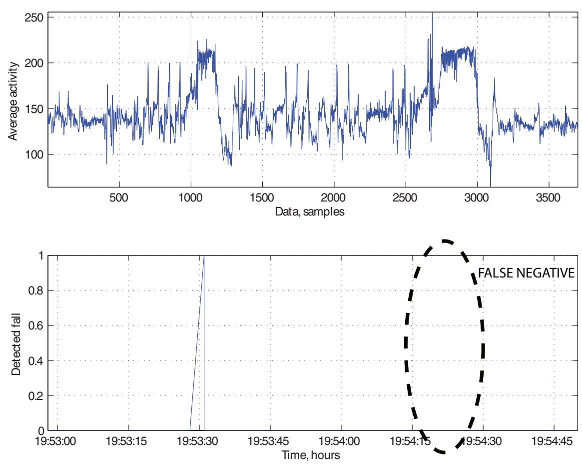

Fig. 4. A data cut demonstrating True Positive (TP) and False Negative (FN) algorithm results

According to overall statistics (see Table I), there were 5 false negative cases when the fall was not detected during the monitoring. We try to clarify the reason why system failed and examine both TP and FP cases, where both acceleration values correspond to a fall behavior (see Figure 4). In occurred situation, algorithm triggers further processing and orientation check. However, in the second case, posture was not identified as horizontal and therefore, alarm was not fired. We explain this exception by singularity of the developed algorithm and particular behavior of volunteers during the test. The system is set to provide a few seconds time gap between the impact and orientation check to separate two different phases. In many cases, a person would quickly change the orientation of the body (e.g stand up) precisely after fall occurred which system identifies as true negative. A simple and straightforward approach to avoid this issue is to reduce an above mentioned time gap. Moreover, this will not be a problem in case of elderly people, when the fall is more fixed and recovery period is significantly longer. In either case if the person was able to stand up immediately after the fall, this situation can still be detected from activity variation but does not have to be reported as an emergency alarm.

Besides from alarm generation, system can be configured to perform the consistent monitoring of pulse and oxygen saturation. These data can be subsequently transfered to the server, stored in the database and accessed by caregivers. In this case, medical personnel can not only observe the alarm list, but also follow the variation of physiological data and analyze its behavior before or after the fall.

IV. Conclusion

Following the recent demand in independent living for elderly people in the modern healthcare, we developed an algorithm for automatic fall detection system with physiological data monitoring. The technique was implemented on the smart-phone platform running android operating system and carries out collecting, storing and processing of acceleration data. In case of fall incident, system generates an alarm and informs remote caregiver about patients current location. High reliability of the developed system is proven during evaluation part where algorithm showed 90% sensitivity, 100% specificity and 94% accuracy. Monitoring process is complemented with physiological data such as heart rate and oxygenation collected via external sensor. This features gives a better insight on fall tendency and tracks essential medical parameters before and after the incident.

However, the fact that certain amount of falls were not detected by the system opens possibilities for further improvements. One possible approach is to tune impact and orientation thresholds depending on the monitoring purposes and conditions. Adding extra parameter such as velocity can improve the algorithm performance, but affect the computational demand at the same time. One of the most reasonable paths for future development is integration with a smart home system, a part of the ambient assisted living area with a specific aim of monitoring health, safety and well-being of the patient. For example a fall alarm, occurred during the monitoring process can trigger the system to check current location of the patient inside smart home, how much time passed since he/she was moving and which service was enabled before the fall occurred (e.g. television, microwave or training simulator). It will improve the overall performance of the system, decrease emergency response time and give a better insight on falling behavior in general.

Another essential approach for the future work is expansion of the experimental part of the studies. We can perform data collection in different study cases according to the multiple life-like scenarios. As it was previously mentioned, the current testing results were obtained mainly for evaluation of the developed fall detection algorithm. However, if we want to perform sophisticated analyses involving the physiological data and have a better insight on its correlation with the fall accidents, it is essential to perform long-term experiments.

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