An Enhanced Fall Detection System using Android based Smart Phone

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Abstract: Due to their widespread popularity, decreasing costs, built-in sensors, computing power and communication capabilities, Android-based personal devices are being seen as an appealing technology for the deployment of wearable fall detection systems. In contrast with previous solutions in the existing literature, which are based on the performance of a single element (a smart phone), this paper proposes and evaluates a fall detection system that benefits from the detection performed by two popular personal devices: a smart phone and a smart watch (both provided with an embedded accelerometer and a gyroscope). In the proposed architecture, a specific application in each component permanently tracks and analyses the patient's movements. Diverse fall detection algorithms (commonly employed in the literature) were implemented in the developed Android apps to discriminate falls from the conventional activities of daily living of the patient. As a novelty, a fall is only assumed to have occurred if it is simultaneously and independently detected by the two Android devices (which can interact via Bluetooth communication). The system was systematically evaluated in an experimental tested with actual test subjects simulating a set of falls and conventional movements associated with activities of daily living. The tests were repeated by varying the detection algorithm as well as the pre-defined mobility patterns executed by the subjects (i.e., the typology of the falls and nonfall movements). The proposed system was compared with the cases where only one device (the smart phone or the smart- watch) is considered to recognize and discriminate the falls. The obtained results show that the joint use of the two detection devices clearly increases the system's capability to avoid false alarms or 'false positives' (those conventional movements misidentified as falls) while maintaining the effectiveness of the detection decisions.

Keywords: Fall detection, smart phone-based application, multiple kernel learning, accelerometer, power consumption, Android App.

I. INTRODUCTION

Unintentional injuries caused by falls among seniors are a major public health problem. According to different reports from the World Health Organization [1,2], a significant proportion (28%–35%) of the population over 64 suffers a fall per year. Direct medical costs associated with falls among American older people surpassed \$20 billion in 2010 [3], an amount that is expected to reach \$67.7 billion by 2020 [4].

A quick medical response after a fall occurrence has been proven to be key to reduce the morbidity and mortality of falls [5]. Therefore, the deployment of automatic, reliable and cost efficient Fall Detection Systems (FDS) has become a significant research topic during the last decade.

FDS, which can be regarded as an example of the application of Ambient Intelligence (AmI) paradigm to healthcare [6], can be classified into two general typologies [7]: context-aware and wearable systems. Context-Aware Systems (CAS), which include both vision-based and ambient-based architectures, are Wireless Sensor Area Networks [8] that analyze the signals captured from cameras, microphones and other environmental sensors [9], which are seamlessly placed around the patient to be tracked. CAS solutions present several drawbacks. Firstly, the zone where the patient is monitored is constrained to the specific area in which the sensors are installed. Uncontrollable circumstances in this area (changes in the illumination, noise, visual obstacles, falling objects, etc.) may alter the effectiveness of the detection. In addition, the set- ting up, tuning and maintenance of a CAS normally entail a nonnegligible cost whereas the permanent visual observation of the system may compromise the patient's sense of privacy. On the contrary, wearable FDS employ sensors (usually accelerometers) which are integrated in the clothes or transported by the patients as garments or personal gadgets. Wearable solutions directly measure physical variables describing the user's movements without depending on the particularities of a restricted monitoring zone. In fact, if the transported devices incorporate wide area communication interfaces (e.g. a 3G/4G connection), the patient can be monitored almost in a ubiquitous way. Thus, wearable detection systems can be considered as a specific case of medical Body Area Networks (BANs) [10]. In this sense, wearable FDS can benefit from the computing capacities, embedded sensors and diversity of communication interfaces that are integrated in today's smartphones. Smartphones are increasingly being proposed [11, 12] as sensing and computing elements in cloudassisted BANs aimed at tracking and processing the data flowing from body sensors both offline and online. In the area of fall detection, the rapidly declining prices and popularity of these devices have stimulated many research studies and projects proposing smartphone-based FDS over the last five years. In most cases, these proposals consist of 'stand-alone' architectures where the smartphone is the only element in the system, simultaneously acting as a sensor, communication gateway, alarming hardware and computing unit (to decide if a fall has occurred).

The chest and the waist have been proven [13] to be the best positions to place a wearable accelerometer aimed at detecting falls accurately, as they are typically close to the center of gravity of the human body. Some studies [14] have shown that the use of pockets to keep the smartphone diminishes the effectiveness of the detection procedure, as long as the device may move freely within the pocket and reduce the capability of the built-in accelerometer to characterize the mobility of the user. Thus, in some proposals in the literature, the detection systems yield optimal results only if the smartphone is fixed to these positions (chest or waist) with an adjustable band or a similar fixing element. However, this tight attachment of the phone clearly affects the patient's comfort while hampering the freedom of using the conventional functions of the smartphone.

On the other hand, programmable commercial smart watches, which can integrate accelerometers too, have also been proposed as an economical alternative to deploy wearable FDS [15–17]. When compared to smartphones, smart watches improve the ergonomics of the system and (normally) the resolution and range of the employed built-in accelerometers. Conversely, the motion of the wrists (where the smart watch is fastened) is not always representative of the body stability. So, sudden or abrupt movements of the arms that are not necessarily caused by falls may easily induce false positives (that is to say, activities that are misidentified as falls).

In order to higher reach a effectiveness and confidence of the fall detection decision, we pro- pose a FDS that integrates two commercial Android devices: a smartphone and a smart watch. Google's Android is definitely the most extended Operating System (OS) for smartphones with a 82.8% market share during the second quarter of 2015 [18]. As a consequence, Android is being massively utilized as the programming environment for the development of mobile medical and social networks [19] and, in particular, of most smartphone-based fall detection systems that can be found in the literature [20].

II SYSTEM STUDY

Abbate et al. proposed a SP-based fall locator that utilizes a blend of TBM and ANN [9]. Notwithstanding the revealed 100% characterization execution in disconnected examination, the informational collection utilized for preparing and testing the ANN (86 examples little altogether). was presentation of the Additionally, the application (bogus alerts rate and battery utilization, in actuality, situations, normally known as online examination, was not introduced. All the more as of late, Kerdegari et al. built up an Android application, SFD, based on the thought of multi-layer perceptron (MLP) neural organization for fall identification occasion [17]. During disconnected investigation, their calculation accomplishes 92:03% affectability, 91:07%

particularity, and 91:06% precision on information recorded around the abdomen. In case. when applied for online any examination, the framework execution somewhat debases as far as explicitness (93:18% affectability, 88:88% particularity, and 91:25% precision). Extra to the long framework choice time (at any rate 30 s for calculation choice + 60 s default time for ready undoing), no particular data on the bogus alert rate regarding the situation of the SP is given. In the current framework, if the foes need to do mystery keys assault, they can't discover the break through PUFs which isn't attainable in all actuality. The current doesn't give a quality based encryption. The proposed framework presents a robotized superior SP-put together fall location centering framework with respect to pragmatic issues, for example, client comfort utilization. and force The proposed independent fall finder is created as an Android application, specifically FallDroid, which utilizes the accelerometer sensor implanted in SPs. The planned application gives an elderfriendly GUI and supports the two most advantageous SP conveying areas: midriff (belt/pocket) and thigh (gasp pocket).

In examination with ML procedures, the proposed calculation two-venture is demonstrated to be more force productive. In the initial step, a low computational cost approach dependent on TBM is utilized, trailed by the example acknowledgment method, different piece learning support vector machine (MKL-SVM) in the second step which is infrequently summoned. The battery utilization was dissected and detailed various situations. The recorded for informational indexes were procured from human preliminaries directed deliberately in both, lab and free living conditions. At long last, we report the disconnected and online order results on fall-like ADLs, for example, lying on the floor, abrupt stop subsequent to

strolling, incidentally hitting the sensor and so on to exhibit the better execution of the introduced framework. The framework proposed a security property is exceptionally alluring as the asset sharing climate might be inclined to different sorts of Fall location. The framework is more made sure about as every sensor in shrewd body sensor network has the property innately to character fall itself; we place the potential for the sensor to be utilized to create mystery keys for information encryption.



III METHODOLOGY

FallDroid is designed as a standalone and user independent fall detection system that actively runs in the background and uses a two-step algorithm (described in subsection II-B) to analyze subject movement. Upon fall detection, the application triggers the SP to vibrate and an alert cancellation page appears on the screen. Unless canceled within a specified time period (default setting of 30 s) by the user, a sound alarm is activated followed by a help text message containing location information being sent to specified emergency contacts.

FallDroid Implementation

FallDroid has been developed using Android Studio IDE with min API 17 and target API level 23. The GUI of application consists of four screens: the main page, settings, fall alert cancellation, and feedback. The layout is designed to facilitate usability by the elderly with an overall focus on reducing battery power consumed particularly for unnecessary computations. In what follows, we highlight the main services provided by the application.

Configuration and Control: The main page of the application serves three functions: (i) start/stop the fall detection process, (ii) application configuration settings, and (iii) summarized display critical/crucial of settings. Once the user starts the sensing process, a notification icon will appear on the top left corner of the screen in the notification bar. The icon remains visible as long as the application is running in the background. The settings page can be used to customize personal details, location of the SP being carried, fall detection service priority, and settings related to fall alert notification. Settings for fall alert notification comprise of alarm sound and duration, countdown timer for alert cancellation, and entries for emergency contacts. Changes made to any user-specified setting can be seen immediately under the settings summary section on the main page. The settings are saved using the Shared Preferences class which permits previous settings to persist over multiple sessions as well as after SP reboots.

Fall Detection Service: The algorithm proposed for fall detection is implemented as an Android service, using the Intent Service class that can run continuously in the background irrespective of the application. The intent service runs the algorithm in its own separate worker thread without blocking the main UI thread which otherwise can make the application non-responsive. Once the service is activated, it instantly acquires the PARTIAL_WAKE_LOCK, which pre-

vents the CPU from going into sleep mode when the phone is idle. Subsequently, the algorithm checks the device accelerometer and its sensing capabilities. Once found, it registers the Sensor Event Listener to receive motion data from the accelerometer at a desired sampling rate. The incoming sensor data values are stored in a linked-list queue following the First-In-First-Out (FIFO) discipline, and maintain data history of up to 6 s. As further explained in sub-section II-B, initial steps of the TBM algorithm use this data to detect fall like events. Upon detection, the rest of the algorithm is then executed. The parameters associated with pre-trained MKL-SVM are not hard-coded but instead provided via a file. In this manner, application personalization or update is facilitated by replacing the parameters file with a new one.

Notification System: When a fall event is detected by MKL-SVM, the SP starts vibrating followed by an automatic launch of the fall alert cancellation page. The user has a default period of 30 s to cancel the false alert in case an ADL event is mis-classified as fall. If the user cancels the alert, the application then requests for feedback through the feedback page. The entered data is stored in a file which can later be used for further analysis improve the algorithm to performance.

IV ARCHITECTURE

As aforementioned, the developed system, which is sketched in Fig, includes two basic elements: a smart watch and a smartphone both provided with Android Operating System and embedded mobility sensors (a triaxial accelerometer and a gyroscope).

The selected smartwatch was a LG W110 G Watch R model, with 1.2GHz Qualcomm Snap- dragon 400 MSM8226 1.2 GHz processor, 512 MB of RAM, 410 mAh

battery capacity and 4GB of internal storage. Although the system has also been tested with other smartphone models, the employed smartphone was a LG Nexus 5. This phone features a Qualcomm Snap- dragon 800 2.26 GHz processor and 2 GB of RAM while it is powered by a 2300 mAh battery.



Fig: Basic Architecture of Fall Detection System

V COMPONENTS

Each device carries out its own monitoring process independently. For that purpose, an Android application (*app*) was programmed to implement the different detection algorithms (which are described in the subsection 2.1) and installed in both devices. *Apps* are permanently tracking the user's movements based on the data received from the accelerometer and the gyro- scope that are embedded in the wearable devices.

The smartwatch and the smartphone incorporate short-range Bluetooth communications. Other wireless standards (802.15.4/ZigBee, 802.15.6 or Ultra-low power Wi-Fi) that are typically employed in healthcare BANs, are not considered because they are not commonly provided by commercial smart watches or smartphones. The low scalability of Bluetooth net- works (which may pose an important problem in other body area networks with multiple sensing motes) is irrelevant as the proposed network just consists of two nodes. specification Moreover, the Bluetooth natively implements different mechanisms at different layers (authentication, confidentiality, authorization, etc.) to guarantee secure communications, which is a crucial concern for the viability of any mhealth (mobile health) sensor network and medical BANs.

In the proposed system, as soon as a fall is detected by the *app* in the smart watch an alerting message is transmitted to the smartphone via Bluetooth. A fall is only assumed to have occurred if the *app* running in the smartphone also detects a fall event within a short interval of 1 s before or after the reception of this message. In that case, a local acoustic alarm is trig- gered in the smartphone. If this local alarm is not deactivated by the user before 20 s, an automatic emergency call (or a text message) is sent to a preset contact phone number.

Accordingly, aiming at reducing the occurrence of false positives, the procedure for remote alerting is not initiated if the detection is only accomplished in a single device.

VI CONCLUSION

This paper proposes and evaluates a fall detection system that benefits from the detection performed by two popular personal devices: a smart phone and a smart watch (both provided with an embedded accelerometer and a gyroscope). In the proposed architecture, a specific application in each component permanently tracks and analyses the patient's movements. In the future a diverse fall detection algorithms (commonly employed in the literature) will be implemented in the developed Android

discriminate falls apps to from the conventional activities of daily living of the patient. As a novelty, a fall is only assumed to have occurred if it is simultaneously and independently detected by the two Android devices (which can interact via Bluetooth communication). The system was systematically evaluated in an experimental tested with actual test subjects simulating a set of falls and conventional movements associated with activities of daily living.

VII REFERENCES

[1] Ageing WHO, Unit LC. WHO global report on falls prevention in older age. World Health Organization; 2008.

[2] Yoshida S. A Global Report on Falls Prevention Epidemiology of Falls [Internet]. World Health Organi-zation. 2007. Available:

http://www.who.int/ageing/projects/1.Epidem iology of falls in older age.pdf.

[3] Stevens JA, Corso PS, Finkelstein EA, Miller TR. The costs of fatal and non-fatal falls among older adults. Inj Prev. National Center for Injury Prevention and Control, Centers for Disease Control and Prevention, Atlanta, GA, USA.; 2006 Oct; 12(5):290–5.

[4] CDC (Centers for DC and. Costs of Falls Among Older Adults [Internet]. Report of the Injury

Center.Available:http://www.cdc.gov/Homea ndRecreationalSafety/Falls/fallcost.html.

[5] Noury N, Fleury A, Rumeau P, Bourke AK, Laighin GO, Rialle V, et al. Fall detection-principles and methods. In: Dittmar A, Clark J, editors. Proceedings of the 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBS 2007). Lyon, France: IEEE; 2007. p. 1663. [6] Acampora G, Cook DJ, Rashidi P, Vasilakos A V. A survey on ambient intelligence in healthcare. Proc IEEE. IEEE; 2013; 101(12):2470–94.

[7] Mubashir M, Shao L, Seed L. A survey on fall detection: Principles and approaches. Neurocomputing. Elsevier; 2013; 100:144– 52.

[8] Zeng Y, Li D, Vasilakos A V. Real-time data report and task execution in wireless sensor and actuator networks using selfaware mobile actuators. Comput Commun. Elsevier; 2013; 36(9):988–97.

[9] Zhou L, Naixue X, Shu L, Vasilakos A, Yeo S-S. Context-Aware Middleware for Multimedia Services in Heterogeneous Networks. IEEE Intell Syst. IEEE; 2010; 25(2):40

[10] Chen M, Gonzalez S, Vasilakos A, Cao H, Leung VC. Body area networks: A survey. Mob networks Appl. Springer-Verlag New York, Inc.; 2011; 16(2):171–93.

[11] Fortino G, Di Fatta G, Pathan M, Vasilakos A V. Cloud-assisted body area networks: state-of-the-art and future challenges. Wirel Networks. Springer; 2014; 20(7):1925–38.

[12] Almashaqbeh G, Hayajneh T, Vasilakos A V, Mohd BJ. QoS-aware health monitoring system using cloud-based WBANs. J Med Syst. Springer; 2014; 38(10):1–20.

[13] Fang S-H, Liang Y-C, Chiu K-M. Developing a mobile phone-based fall detection system on android platform. In: BenLetaief K, Zhang Q, editors. Proceedings of the Computing, Communications and Applications Conference (ComComAp). Hong Kong, China: IEEE; 2012. p. 143–6. [14] Kau L, Chen C. A Smart Phone-based Pocket Fall Accident Detection, Positioning and Rescue System. In: Lee M-H, Chang W, editors. IEEE International Symposium on Bioelectronics and Bioinformatics (ISBB). Chung Li, Taiwan: IEEE; 2014. p. 1–4.

[15] Maglogiannis I, Ioannou C, Spyroglou G, Tsanakas P. Fall Detection Using Commodity Smart Watch and Smart Phone. In: Maglogiannis IL, Papadopoulos H, Sioutas S, Makris C, editors. Artificial Intelligence Applications and Innovations. Springer; 2014. p. 70–8.

[16] Honglun H, Meimei H, Minghui W. Sensor-based wireless wearable systems for healthcare and falls monitoring. Int J Smart Sens Intell Syst [Internet]. 2013;6(5):2200– 16. Available: http://www.scopus. com/inward/record.url?eid=2s2.0848930168 37&partnerID=40&md5=2413da25b117d24 472805e83dff161e3

[17] Tan T-H, Gochoo M, Chang C-S, Wu C-T, Chiang JY. Fall Detection for Elderly Persons Using Android- Based Platform. In: Park S-T, Tsoy EB, Pestryakov AN, editors. Proceedings of the 8th International Forum on Strategic Technology (IFOST 2013). Ulaanbaatar, Mongolia; 2013.

[18] IDC. IDC Worldwide Mobile Phone Tracker (May 2015) Available: http://www.idc.com/.

[19] Zhang D, Zhang D, Xiong H, Hsu CH, Vasilakos A. BASA: Building mobile Ad-Hoc social networks on top of android. IEEE Netw. IEEE; 2014; 28(1):4–7.

[20] Casilari E, Luque R, Morón M. Analysis of android device-based solutions for fall detection. Sensors [Internet]. 2015 [cited 2015 Sep 9]; Available: http://www.mdpi.com/1424-8220/15/8/17827/pdf Prakasam Dist, Affiliated to Jawaharlal Nehru Technological University, Kakinada.

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