Simultaneous Real-Time Human Fall Detection and Reidentification Based on Multisensors Data

Bastico Matteo
Universidad Politécnica de Madrid
Madrid, Spain
mab@gatv.ssr.upm.es

Ruiz Bejerano Verónica
Universidad Politécnica de Madrid
Madrid, Spain
vrb@gatv.ssr.upm.es

Belmonte-Hernández Alberto
Universidad Politécnica de Madrid
Madrid, Spain
abh@gatv.ssr.upm.es

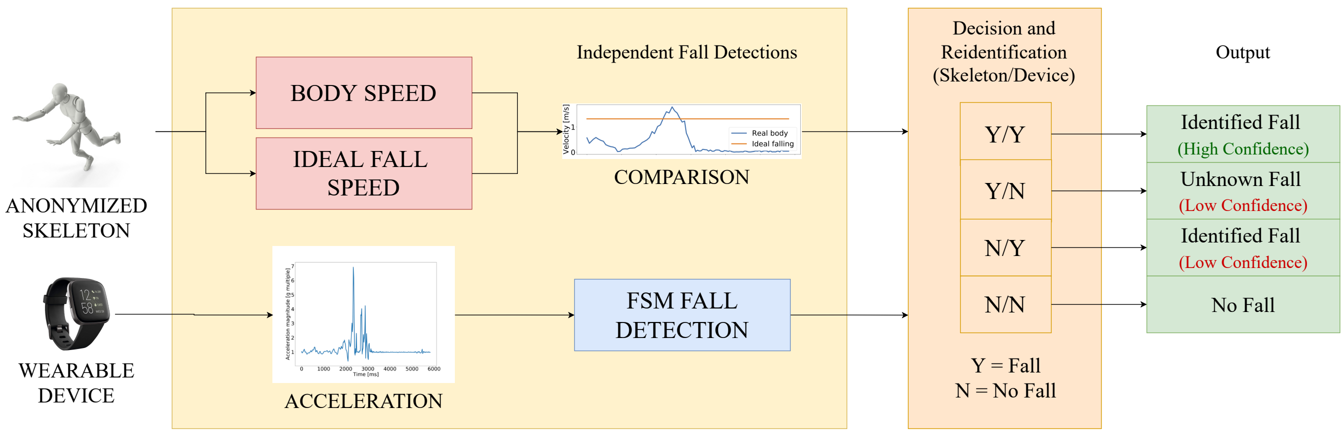


Figure 1: Overall system architecture block diagram. (Red) Skeleton fall detection mechanism. Firstly, the body speed and the ideal falling speed are computed from the skeleton positions acquired by the skeleton tracking camera. The two velocities are compared in order to obtain candidate falls. (Blue) Simultaneous independent fall detection using acceleration data from wearable devices. (Orange) Given the two outputs (Y=Fall, N=No Fall), the final decision is taken and reidentification is done, if possible. Four different outputs are possible (Green).

ABSTRACT

Fall detection and reidentification are active areas of research with a wide variety of applications in many fields. Nowadays, wearable devices capable of recording multisensors measurements are being increasingly introduced in people's daily lives, such as smartphones and smartwatches. Often, these devices are used in healthcare rehabilitation scenarios to monitor patients activities and, eventually, detect important events like falls. In some cases, the equipped Inertial Measurements Unit (IMU) lacks of gyroscope and magnetometer, allowing to acquire only accelerations measures. In this conditions, the detection tasks become more complex and many false detections can arise. Additionally, other methods, such as monitoring cameras, are usually used in the environment to overcome this problem and further track the patients. But, due to the lack of personal identifiers in the camera tracking system, it is not straightforward to associate falls, when detected, to a particular person. In this paper, we propose a complete real-time system to detect falls reducing false positives and simultaneously reidentify the patients using 3D skeleton points, given by a tracking camera, and 3-axis accelerometer data. Firstly, the system performs fall detection by means of a mathematical analysis of the skeleton points evolution along different frames. At the same time, fall detection is computed on the acceleration data using a Finite State Machine approach. If a fall is detected with both mechanisms, reidentification is carried out to associate the skeleton with the wearable device. A dataset of fall sequences has been recorded and is available for testing purposes. The final accuracy of our fall detection and reidentification algorithm is 100% on our dataset.

CCS CONCEPTS

• **Applied computing → Health care information systems**.

KEYWORDS

Fall detection, Reidentification, Multisensor Data, Accelerometer, 3D Skeleton Joints, Matching

ACM Reference Format:
Bastico Matteo, Ruiz Bejerano Verónica, and Belmonte-Hernández Alberto. 2022. Simultaneous Real-Time Human Fall Detection and Reidentification Based on Multisensors Data. In *The15th International Conference on PErvasive Technologies Related to Assistive Environments (PETRA '22), June 29-July 1,*

PETRA '22, June 29-July 1, 2022, Corfu, Greece

ACM ISBN 978-1-4503-9631-8/22/06…$15.00
https://doi.org/10.1145/3529190.3534728

2022, Corfu, Greece. ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3529190.3534728

1 INTRODUCTION

Falls are a major source of morbidity and mortality in older patients [44]. Following the study of [38, 46], nearly 28-35% of people aged 65 years and above fall each year and this percentage increases to 32-42% for those over 70 years of age. According to the World Health Organization (WHO), an estimated 684,000 fatal falls and approximately 37.3 million falls severe enough to require medical attention occur each year [39]. For example, estimates for fall-related hip fractures are 250,000 annually, a number that is expected to double by the year 2040 [34]. According to these numbers, it is clear that an effective system to detect falls, and consequently send alarm reports, is needed in order to dispatch fast rescue. This need exponentially increases in monitored environments, such as nursing and patients/caregiver's homes, where elderly residents are looked after. With the advancement of information technology, the concept of smart rehabilitation clinics has gradually become a reality [11]. Information technologies, such as automation, Artificial Intelligence (AI) and telemedicine are being employed in future-ready smart clinics. Human motion monitoring and tracking can improve the patients rehabilitation process allowing them to restore their functional capability to normal [8, 60]. Home healthcare operations have been introduced recently to consider elderlies' preferences willing to receive their cares at their homes instead of hospitals and to reduce the time and cost for patients going often to clinics [4, 15]. Home healthcare makes also possible to remotely monitor the life activities of the elderly [22] and detect risky events in real-time, such as falls [52, 57] or wandering behaviours [26].

During the past decades, much effort has been put into these fields to improve the accuracy of fall detection and prediction systems as well as to decrease the false alarms [53, 58]. This task mainly consists in analysing patterns provided by smart wearable body sensors [2] or environmental sensors, such as surveillance and depth cameras. The RGB images and Depth information recorded by the cameras are often used to extract features and can provide a wide variety of information regarding the detected subjects. Due to security and privacy issues, the images cannot be stored and must be processed in real-time, reducing the available features and increasing the solution complexity [18, 35]. To overcome these issues, various techniques have been proposed to extract anonymized skeletons from the images [31, 41]. Such procedure is used in this work to obtain skeleton points from RGB/depth camera frames through a tracking system.

On the other side, wearable devices, e.g. smartwatches, can collect health status and movement information of the patients, such as heart rate and acceleration measurements. This data has the advantage of being provided directly with a unique anonymized identifier, e.g. MAC address or device name. Therefore, in contrast to the camera, the identification of the patients can be done straightforward. In this multisensor's scenario, reidentification to match measurements provided by different sensors is needed to relate detected events to a same person. The most used approach is to find similar patterns between measurements of different nature transforming them into a common space in order to make a direct comparison possible [5, 48]. Nevertheless, limited budgets affect the quality of the employed devices. It is not uncommon that wearable devices lack of important IMU components, such as magnetometer and gyroscopes, providing only accelerations measurements [25]. In a fall detection perspective, using less information, the risk of false positives is very high and the association with a skeleton is more difficult.

The main goal of our system is to achieve real time identification when a fall event is triggered using both cameras and wearable sensors to reduce the number of false alarms. A software that directly recognize subjects in the images [37, 51, 56] is not always implementable due to its computational needs, legal issues [36] or lack of ground-truth information. To respect privacy policies and reduce the computational needs, we implemented our architecture using only a subset of points from the skeletons and the acceleration data from the wearable device. The entire computational core relies on fast mathematical computations and comparisons which allow to speed up the analysis in a real-time environments.

2 RELATED WORKS

In the literature, several systems have been proposed to tackle the problem of fall detection and reidentification between different devices. However, the joint problem, as treated in this work, has barely been covered in the past years. The fall detection task based on wearable devices typically combines accelerometers, gyroscopes and even barometers [54]. Early approaches proposed simple threshold-based algorithms to detect human falls using only a triaxial accelerometer [1, 3, 7, 13, 27]. After that, the methods have been improved adding Hidden Markov Model (HMM) applications [30, 49]. More recently, machine learning and deep learning techniques have been employed to further improve the performances. Palmerini *et al.* [40] used several classifiers to combine features based on the acceleration: Naïve Bayes, logistic regression, KNN, random forests, and SVM. Santos *et al.* [45] also proposed a simple Convolutional Neural Network to solve the fall detection task.

To reduce the number of false positives in the detection, the combined information from various sensors of the same wearable device can be used. In particular, accelerometer and gyroscope [19, 23, 29, 42] or barometer [9, 47] are often coupled in the algorithms. In this work, due to important limitations in the hardware budget, only raw accelerometer measurements are available in the employed wearable devices.

More deep learning approaches have been considered for the image-based, and especially skeleton-based, fall detection task. Often, the algorithms are based on motion recognition [14, 59] even if, in some cases, it is difficult to distinguish between a fall and basic Activities of Daily Living (ADL), e.g. sleeping. Convolutional Neural Networks [55], LSTM [24] and other models [43] have been exploited to perform fall detection, extracting features from skeleton points. Alternatively, mathematical solutions using physical quantities, e.g. fall direction, angle and height, have been proposed to better distinguish a fall from other normal daily activities [10, 28]. This work follows the latter approach in order to reduce the computational time of the algorithm and allow fast real-time applications. The falling velocity of the human body is computed and compared with a threshold derived from an ideal physically-calculated fall velocity.

3 SYSTEM ARCHITECTURE

The overall proposed system architecture for simultaneous real-time human fall detection and reidentification is shown in Fig. 1. The system is composed of two main parts. In the first one, depicted in green, skeleton data acquired by a tracking camera is used to estimate the body velocity and an ideal falling velocity by means of simple mathematical calculus. The velocities are compared to detect potential falls only from the skeletons data. Simultaneously, fall detection is performed on the acceleration data from the on-wrist wearable device through a Finite State Machine (FSM) mechanism (block in Blue). Finally, the outputs of the two algorithms are compared in the last block (Red) to confirm the fall and, subsequently, perform reidentification in order to associate the event with a particular person in the environment. In the following, after formally stating the problem, we describe the two main phases of our system in detail.

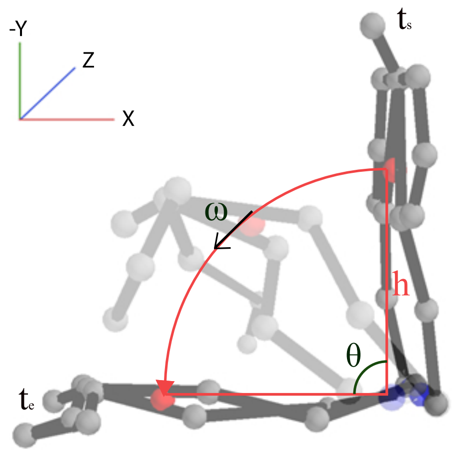
3.1 Problem Statement

In a typical indoor scenario, the skeleton tracking camera is placed parallel to the ground at an height between 1.2 and 1.5 meters. Its coordinate system is denoted with X, Y and Z. By construction, Y is pointing to the ground while X and Z are parallel to the floor [20]. A patient wears the smartwatch on the left wrist to measure the acceleration and its axis are indicated with x, y and z. According to [16], the x and y axis are parallel to the device screen. The first one is aligned with the top and bottom edges in the left-right direction while the y axis is aligned with the left and right edges in the top-bottom direction. The z axis is perpendicular to the device's screen, pointing up.

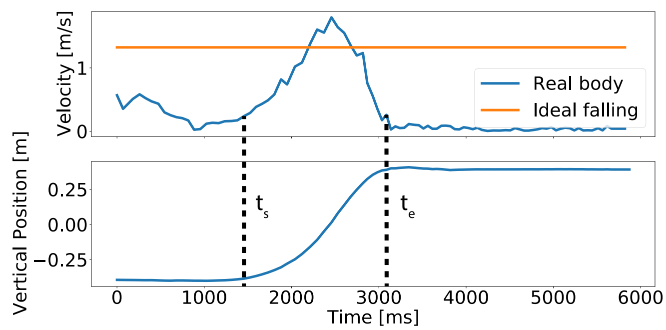
Given the raw data collected in real-time, when a fall is detected, it is not straightforward to create an association between the skeletons and the accelerations measured by the wearable devices. The aim of this work is to develop an entire system to perform fall detection using the aforementioned devices and, once the fall is confirmed, associate the event to a particular person identifier.

3.2 Skeleton Fall Detection

Our ideal 2D model of free-space human fall is shown in Fig. 2a. We consider only the time interval between the start and the end of the fall, namely $[t_s, t_e]$. We define two skeleton key-points for our algorithm: (1) the body center point, $\boldsymbol{c}$, defined as the centroid between the left, right hip and chest (2) the ankles point, $\boldsymbol{a}$, defined as the geometrical center between the two ankles points. The two key-points are represented, respectively, in red and blue on Fig. 2a. To compute the body center, we decided to use the points more likely associated with a rigid body movement during a human fall in order to avoid estimation errors. Let h be the vertical distance between the two key-points and θ the angle described from the beginning to the end of the fall, namely from t_s to t_e. The angular velocity of the body center point can be easily computed as $\omega = \theta/(t_e - t_s)$. The linear velocity associated with an ideal fall in the 2D plane is then $v = h\omega$. The human falling speed computed in this way can be considered as a lower bound approximation of a real fall speed,



(a)



(b)

Figure 2: Skeleton model of human real fall. In 2a the ideal fall in 2D, starting from the initial position at t_s the body reaches the floor at t_e. Considering the central body point (in red), the trajectory is circular with radius h, total angle θ and angular speed ω. The blue point, representing the average between ankles positions, is used to compute the radius. In 2b, the vertical position (Y-axis of camera) of the body center point during a fall, on the bottom, and its velocity module computed thought derivative on the top. The ideal fall speed is also depicted, as well as, the starting and ending time of the fall.

since we considered a null initial velocity at time t_s. Eventually, a compensation, ϵ, can also be taken into account to consider frictions of the environment, e.g. air friction. Therefore, we define the ideal falling speed lower bound as $v_L = v - \epsilon$.

In a real 3D fall, the body center point spans the three dimensions during the event. It is always possible to rotate the system coordinates so that the fall trajectory is parallel to a plane which can be approximated to our ideal 2D model. Let $C = \{\boldsymbol{c}_t | t_0 \le t \le t_1\}$ be the set of 3D positions of the center body key-point during an analysed time interval (t_0, t_1), its speed at each time instant can be computed by differential calculus. Such velocity has a component in each coordinate of the 3D space and we use its magnitude as measure of comparison with the ideal falling speed v_L. Given the body center speed at time t, $\boldsymbol{v}_t = (v_{X,t}, v_{Y,t}, v_{Z,t})$, we detect a fall if and only if

$$|\boldsymbol{v}_t| = \sqrt{v_{X,t}^2 + v_{Y,t}^2 + v_{Z,t}^2} > v_L = h\frac{\theta}{t_e - t_s} - \epsilon. \quad (1)$$

The starting and ending fall times, t_s and t_e, can be computed by seeking the beginning and end of a significant jump in the vertical position of the central point along the time window, as shown in Fig. 2b (bottom). Based on the trends in average adult human height in [6], we define a minimum variation of $70cm$ in order to consider Eq. 1 for candidate falls. Finally, the fall angle, θ, is calculated from the positions at the beginning and end of the candidate fall. A graphical representation of the proposed method on a real fall is shown in Fig. 2b (top).

Note that this computation makes the skeleton fall detection independent from the distance between body and camera since both sides of the equation are computed proportionally to it, i.e h and $\boldsymbol{v}_t$.

3.3 On-wrist Wearable Device Fall Detection

Abate *et al.* [1] proposed a method based on a Finite State Machine (FSM) to represent the acceleration dynamics within a fall using a smartphone-based system. Following this work, Khojasteh *et al.* [27] improved the previously proposed fall detection system using an on-wrist wearable accelerometer. In this paper, as in [50], we choose the latter extension to cover a wider variety of publications.

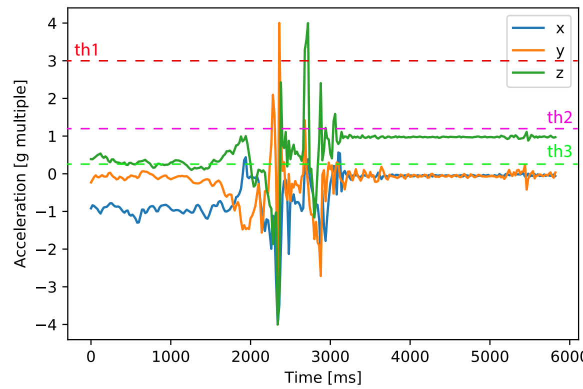
Let $\boldsymbol{a}_t = (a_{x,t}, a_{y,t}, a_{z,t})$ be the acceleration measured at time t by a wearable device in its coordinates system, we define the acceleration magnitude as

$$a_t = \sqrt{a_{x,t}^2 + a_{y,t}^2 + a_{z,t}^2}. \quad (2)$$

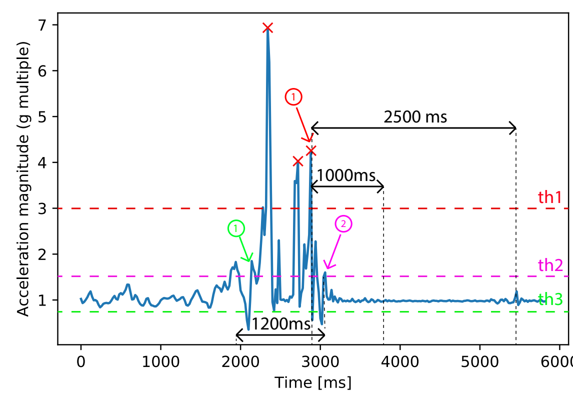
Let us assume that gravity is $g = 9.8m/s^2$. To perform fall detection using only acceleration measurements, we search for a peak in the acceleration magnitude at time t_p. This peek has to be higher than $th1 = 3 \times g$ and followed by no other peak in the period $(t_p, t_p + 2500ms)$, i.e. not higher than $h1$. For more details of the used FSM please refer to [1, 27, 50].

3.4 Reidentification

Let the time interval (t_s, t_e) and the time instant t_p be the outputs of the two fall detection algorithms when a fall is detected, with skeleton points and accelerations respectively. Both measurements are automatically given by the two detection procedures, without additional computation, reducing the load on the required time. In particular, the first one is computed to detect candidate falls before considering Eq. 1 and, therefore, it's directly available in case the equation holds. The second is the sought time in which the acceleration magnitude overcomes the threshold $th1$. The original FSM [1, 27] additionally seeks the starting and ending fall times from the acceleration measurements, which are not considered in this work. Finally, the reidentification is performed if the peak time detected on the wearable device is included in the time interval of the skeleton fall, i.e. if $t_s \leq t_p \leq t_e$. The on-wrist wearable device where the peak is detected is then directly associated to the skeleton, assigning a specific human identifier to the fall event.



(a)



(b)

Figure 3: Dynamics of a real fall from our dataset measured through the acceleration with a wearable device located on the left wrist. In 3a the three accelerations components in x, y and z coordinates. In 3b the acceleration magnitude is related with the parameters proposed by [1, 27]. A peak is defined at time t_p (Point 1) if the magnitude of the acceleration is higher than $th1 = 3 \times g$ and there are no other peak in the following $2500ms$. The impact end (Point 2) is defined as the last time in which the acceleration is higher than $th2 = 1.5 \times g$. Finally, the impact start (Point 3), is computed as the time of the first sequence of an acceleration lower than $th3 = 0.8 \times g$ followed by a value higher than $th2$. The impact start and end must belong to the interval $(t_p - 1200ms, t_p)$ and $(t_p, t_p + 1000ms)$, respectively.

Note that our system works even when one of the two input data is not available, since the simultaneous fall detections are independent one from each other. In a real environment, sometimes, measurements are missing because of devices unpredictable errors. In this case, our algorithm can detect fall events using only single-device data but the reidentification is not possible and the outcome reliability is lower. Moreover, a rescue activity may be initiated even when it is not yet known which person had a fall.

4 RESULTS

The devices considered in this study are the Intel RealSense D435i depth camera with Cubemos skeleton tracking SDK [12, 21], the Azure Kinect [32, 33] and the Fitbit Versa 2 smartband [17] as the wearable device.

To test the proposed system, we generated a dataset of falls in a controlled environment. The falls were simulated by several test subjects wearing a smartwatch while being recorded by a tracking camera, either the Intel RealSense or the Azure Kinect. The two cameras acquire different skeletons points, both in number and position. Our algorithm is based just on a subset of these points and, therefore, we decided to test both cameras in order to monitor the response of the system to different inputs. In total, we acquired 17 falls, 8 with Intel RealSense and 9 with Azure Kinect. Among them, only 10 sequences are coupled with accelerometer data in order to simulate the loss of wearable device information and test the independence of the detection modules.

We assigned empirically the value of the compensation factor ϵ in Eq. 1. Due to the fact that our ideal falling velocity does not consider an initial condition, in the 94% of the cases, i.e., all but one, the skeleton fall is correctly detected even without taking into account ϵ. Assigning $\epsilon = 0.1$ m/s, we obtain 100% of correctly detected falls without generating any false positive in the whole recording session (approximately 20 minutes). The performances of the on-wrist wearable device fall detection implemented in our system have already been provided by its authors [27]. In our dataset, the module of the acceleration in Eq. 2 is always significantly higher than the defined threshold $th1 = 3 \times g$ when a fall occurs, leading to 100% of correct fall detection from the wearable device. Nevertheless, false positives are also detected by the wearable device algorithm. It's precision, calculated as the fraction number of true positive over all the detected positives, is 57,89%. When coupled with the skeleton fall detection, all the false positives are discarded, leading to a precision of 100%.

Finally, after the testing of the two separate fall detection modules, the reidentification has been evaluated. The personal identifier corresponding to a skeleton is manually annotated in our dataset. Again, in the 100% of case the reidentification is performed correctly and the right identifier is assigned to the fall.

The real-time requirement of our system is satisfied since the average computational time needed for the entire process is 0.556 ms. This slow processing time allows fast reporting and rescue dispatching in the case in which a fall is detected.

5 CONCLUSIONS

This work has addressed the lack of personal information when using monitoring cameras in healthcare environments due to security and privacy issues, and proposed a real-time system to overcome it in the context of fall detection. In case a fall has been detected with both a camera and a smartwatch that provides a unique identifier, the system associates the skeleton with the accelerometer data given by the wearable sensor. Therefore, the proposed system is composed of two main parts; the fall detection modules, one per type of data, and the reidentification one.

The system has been tested in a controlled environment, where test subjects wearing a smartwatch performed a series of falls while being recorded by a camera, resulting in a high system accuracy. Results from this work have led to a confirmation of the good performance of both the complete solution and the improvement of the separate modules. Using the complete system, false positives are not detected and reidentification is always carried out correctly on our datasets including falls. In future works, near fall events should be taken into account in order to further discard false alarms. The ideal fall used as comparison baseline in our approach is thought for abrupt falls. Consequently, near fall events and balance loss procedures classification should be included in the future.

ACKNOWLEDGMENTS

This work was supported by the H2020 European Project: Procare4Life https://procare4life.eu/ web Grant no. 875221. The authors are with the Escuela Técnica Superior de Ingenieros de Telecomunicación, Universidad Politécnica de Madrid, 28040 Madrid, Spain (e-mail: mab@gatv.ssr.upm.es, vrb@gatv.ssr.upm.es, abh@gatv.ssr.upm.es).

REFERENCES

[1] Stefano Abbate, Marco Avvenuti, Francesco Bonatesta, Guglielmo Cola, Paolo Corsini, and Alessio Vecchio. 2012. A smartphone-based fall detection system. *Pervasive Mob. Comput.* 8 (2012), 883–899.

[2] Geoffrey Appelboom, Elvis Camacho, Mickey E. Abraham, Samuel S. Bruce, Emmanuel L. P. Dumont, Brad E. Zacharia, Randy D'Amico, Justine Slomian, Jean-Yves Reginster, Olivier Bruyère, and E Sander Connolly. 2014. Smart wearable body sensors for patient self-assessment and monitoring. *Archives of Public Health* 72 (2014), 28 – 28.

[3] Fabio Bagalà, Clemens Becker, Angelo Cappello, Lorenzo Chiari, Kamiar Aminian, Jeffrey M. Hausdorff, Wiebren Zijlstra, and Jochen Klenk. 2012. Evaluation of Accelerometer-Based Fall Detection Algorithms on Real-World Falls. *PLoS ONE* 7 (2012).

[4] Chris R. Baker, Kenneth Armijo, Simon Belka, Merwan Benhabib, Vikas Bhargava, Nathan Burkhart, Artin Der Minassians, Gunes Dervisoglu, Lilia Gutnik, M. Brent Haick, Christine Ho, Mike Koplow, Jennifer Mangold, Stefanie Robinson, Matt Rosa, Miclas Schwartz, Christo Sims, Hanns Stoffregen, Andrew Waterbury, Eli S. Leland, Trevor Pering, and Paul K. Wright. 2007. Wireless Sensor Networks for Home Health Care. *21st International Conference on Advanced Information Networking and Applications Workshops (AINAW'07)* 2 (2007), 832–837.

[5] Alberto Belmonte-Hernández, Vassilis Solachidis, Thomas Theodoridis, Gustavo Hernández-Peñaloza, Giuseppe Conti, Nicholas Vretos, Federico Álvarez, and Petros Daras. 2017. Person tracking association using multi-modal systems. *2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS)* (2017), 1–6.

[6] James Bentham and Mariachiara Di Cesare et al. 2016. A century of trends in adult human height. *eLife* 5 (2016), 1–29.

[7] Alan Kevin Bourke, J V O'Brien, and Gerard M. Lyons. 2007. Evaluation of a threshold-based tri-axial accelerometer fall detection algorithm. *Gait & posture* 26 2 (2007), 194–9.

[8] Zenon Chaczko, Anup Kale, and Christopher Chiu. 2010. Intelligent health care — A Motion Analysis system for health practitioners. *2010 Sixth International Conference on Intelligent Sensors, Sensor Networks and Information Processing* (2010), 303–308.

[9] Diansheng Chen, Yu Zhang, Wei Feng, and Xiyu Li. 2012. A wireless real-time fall detecting system based on barometer and accelerometer. *2012 7th IEEE Conference on Industrial Electronics and Applications (ICIEA)* (2012), 1816–1821.

[10] Weiming Chen, Zijie Jiang, Hailin Guo, and Xiaoyang Ni. 2020. Fall Detection Based on Key Points of Human-Skeleton Using OpenPose. *Symmetry* 12 (2020), 744.

[11] Eric Chu, Steve Yun, and Kristy Yau. 2022. Smart Rehabilitation Clinic. 5 (02 2022).

[12] Cubemos. 2020. Skeleton Tracking SDK Installation Guide. https://dev.intelrealsense.com/docs/skeleton-tracking-sdk-installation-guide [Web; accessed 2022-02-16].

[13] Tran Tri Dang, Hai Truong, and Tran Khanh Dang. 2016. Automatic Fall Detection using Smartphone Acceleration Sensor. *International Journal of Advanced Computer Science and Applications* 7 (2016).
[14] Yong Du, Wei Wang, and Liang Wang. 2015. Hierarchical recurrent neural network for skeleton based action recognition. *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2015), 1110–1118.
[15] Amir Mohammad Fathollahi-Fard, Mostafa Hajiaghaei-Keshteli, and Seyed Mohammad Mirjalili. 2019. A set of efficient heuristics for a home healthcare problem. *Neural Computing and Applications* 32 (2019), 6185–6205.
[16] Fitbit. 2017. Fitbit development: Accelerometer sensor guide. https://dev.fitbit.com/build/guides/sensors/accelerometer/ [Web; accessed 2022-02-16].
[17] Fitbit. 2018. Fitbit products. https://www.fitbit.com/global/es/products/smartwatches/versa [Web; accessed 2022-02-16].
[18] Munkhjargal Gochoo, Fady S. Alnajjar, Tan-Hsu Tan, and Sumayya Khalid. 2021. Towards Privacy-Preserved Aging in Place: A Systematic Review. *Sensors (Basel, Switzerland)* 21 (2021).
[19] Quoc Thien Huynh, Uyen D. Nguyen, Lucia B. Irazabal, Nazanin Ghassemian, and Binh Q. Tran. 2015. Optimization of an Accelerometer and Gyroscope-Based Fall Detection Algorithm. *J. Sensors* 2015 (2015), 452078:1–452078:8.
[20] Intel. 2019. How-to: Getting IMU data from d435i and T265. https://www.intelrealsense.com/how-to-getting-imu-data-from-d435i-and-t265/ [Web; accessed 2022-02-16].
[21] Intel. 2021. Depth camera d435i. https://www.intelrealsense.com/depth-camera-d435i/ [Web; accessed 2022-02-16].
[22] Ahmad Jalal, Shaharyar Kamal, and Daijin Kim. 2014. A Depth Video Sensor-Based Life-Logging Human Activity Recognition System for Elderly Care in Smart Indoor Environments. *Sensors (Basel, Switzerland)* 14 (2014), 11735 – 11759.
[23] Adlian Jefiza, Eko Pramunanto, Hanny Boedinoegroho, and Mauridhy Heri Purnomo. 2017. Fall detection based on accelerometer and gyroscope using back propagation. *2017 4th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI)* (2017), 1–6.
[24] Sungil Jeong, Sungjoo Kang, and Ingeol Chun. 2019. Human-skeleton based Fall-Detection Method using LSTM for Manufacturing Industries. *2019 34th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC)* (2019), 1–4.
[25] Kanitthika Kaewkannate and Soochan Kim. 2018. The Comparison of Wearable Fitness Devices. *Wearable Technologies* (2018).
[26] Rebecca J Kamil, Dara Bakar, Matthew Ehrenburg, Eric X. Wei, Alexandra Pletnikova, Grace Xiao, Esther S. Oh, Martina Mancini, and Yuri Agrawal. 2021. Detection of Wandering Behaviors Using a Body-Worn Inertial Sensor in Patients With Cognitive Impairment: A Feasibility Study. *Frontiers in Neurology* 12 (2021).
[27] Samad Barri Khojasteh, José Ramón Villar, Camelia Chira, Víctor M. González Suárez, and Enrique A. de la Cal. 2018. Improving Fall Detection Using an On-Wrist Wearable Accelerometer. *Sensors (Basel, Switzerland)* 18 (2018).
[28] Xiangbo Kong, Takeshi Kumaki, Lin Meng, and Hiroyuki Tomiyama. 2021. A Skeleton Analysis Based Fall Detection Method Using ToF Camera. *Procedia Computer Science* 187 (2021), 252–257.
[29] Qiang Li, John A. Stankovic, M.A. Hanson, Adam T. Barth, John C. Lach, and Gang Zhou. 2009. Accurate, Fast Fall Detection Using Gyroscopes and Accelerometer-Derived Posture Information. *2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks* (2009), 138–143.
[30] Dong-Soo Lim, Chul-Ho Park, Nam Ho Kim, Sang-Hoon Kim, and YunSeop Yu. 2014. Fall-Detection Algorithm Using 3-Axis Acceleration: Combination with Simple Threshold and Hidden Markov Model. *J. Appl. Math.* 2014 (2014), 896030:1–896030:8.
[31] Xiaolong Liu, Pengyuan Lyu, Xiang Bai, and Ming-Ming Cheng. 2017. Fusing Image and Segmentation Cues for Skeleton Extraction in the Wild. *2017 IEEE International Conference on Computer Vision Workshops (ICCVW)* (2017), 1744–1748.
[32] Microsoft. 2019. Azure Kinect DK documentation. https://docs.microsoft.com/en-us/azure/kinect-dk/ [Web; accessed 2022-02-16].
[33] Microsoft. 2019. Buy the Azure Kinect developer kit – Microsoft. https://www.microsoft.com/en-us/d/azure-kinect-dk/8pp5vxmd9nhq [Web; accessed 2022-02-16].
[34] R. Sean Morrison, Mark R. Chassin, and Albert L. Siu. 1998. The Medical Consultant's Role in Caring for Patients with Hip Fracture. *Annals of Internal Medicine* 128 (1998), 1010–1020.
[35] Christopher Neff, Mat'ias Mendieta, Shrey Mohan, Mohammadreza Baharani, Samuel Rogers, and Hamed Tabkhi. 2020. REVAMP2T: Real-Time Edge Video Analytics for Multicamera Privacy-Aware Pedestrian Tracking. *IEEE Internet of Things Journal* 7 (2020), 2591–2602.
[36] Elaine M. Newton, Latanya Sweeney, and Bradley A. Malin. 2005. Preserving privacy by de-identifying face images. *IEEE Transactions on Knowledge and Data Engineering* 17 (2005), 232–243.
[37] Duc Thanh Nguyen, W. Li, and Philip Ogunbona. 2016. Human detection from images and videos: A survey. *Pattern Recognit.* 51 (2016), 148–175.
[38] World Health Organization. 2007. AGEinG And LifE CoursE , fAmiLy And Community HEALtH WHo Global report on falls Prevention in older Age. (2007).
[39] World Health Organization. 2021. Falls. https://www.who.int/news-room/fact-sheets/detail/falls [Web; accessed 2022-02-16].
[40] Luca Palmerini, Jochen Klenk, Clemens Becker, and Lorenzo Chiari. 2020. Accelerometer-Based Fall Detection Using Machine Learning: Training and Testing on Real-World Falls. *Sensors (Basel, Switzerland)* 20 (2020).
[41] Oleg Panichev and A. M. Voloshyna. 2019. U-Net Based Convolutional Neural Network for Skeleton Extraction. *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)* (2019), 1186–1189.
[42] Arkham Zahri Rakhman, Lukito Edi Nugroho, Widyawan, and Kurnianingsih. 2014. Fall detection system using accelerometer and gyroscope based on smartphone. *2014 The 1st International Conference on Information Technology, Computer, and Electrical Engineering* (2014), 99–104.
[43] Heilym Ramirez, Sergio A. Velastín, Ignacio Meza, E. Fabregas, Dimitrios Makris, and Gonzalo Farias. 2021. Fall Detection and Activity Recognition Using Human Skeleton Features. *IEEE Access* 9 (2021), 33532–33542.
[44] Jeffrey M. Rothschild, D. Bates, and Lucian Leape. 2000. Preventable medical injuries in older patients. *Archives of internal medicine* 160 18 (2000), 2717–28.
[45] Guto Leoni Santos, Patricia Takako Endo, Kayo Monteiro, Élisson da Silva Rocha, Ivanovitch M. D. Silva, and Theo Lynn. 2019. Accelerometer-Based Human Fall Detection Using Convolutional Neural Networks. *Sensors (Basel, Switzerland)* 19 (2019).
[46] Suleiman I. Sharif, Alaa B Al-Harbi, Alaa M Al-Shihabi, Dana S Al-Daour, and Rubian S Sharif. 2018. Falls in the elderly: assessment of prevalence and risk factors. *Pharmacy Practice* 16 (2018).
[47] Marie Tolkiehn, Louis Atallah, Benny P. L. Lo, and Guang-Zhong Yang. 2011. Direction sensitive fall detection using a triaxial accelerometer and a barometric pressure sensor. *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (2011), 369–372.
[48] Kit-Lun Tong, Kun-Ru Wu, and Yu-Chee Tseng. 2021. The Device–Object Pairing Problem: Matching IoT Devices with Video Objects in a Multi-Camera Environment. *Sensors (Basel, Switzerland)* 21 (2021).
[49] Lina Tong, Quanjun Song, Yunjian Ge, and Ming Liu. 2013. HMM-Based Human Fall Detection and Prediction Method Using Tri-Axial Accelerometer. *IEEE Sensors Journal* 13 (2013), 1849–1856.
[50] José Ramón Villar, Camelia Chira, En De, Víctor M. González, Javier Sedano, and Samad Barri Khojasteh. 2021. Autonomous on-wrist acceleration-based fall detection systems: unsolved challenges. *Neurocomputing* 452 (2021), 404–413.
[51] Liang Wang, Tieniu Tan, Huazhong Ning, and Weiming Hu. 2003. Silhouette Analysis-Based Gait Recognition for Human Identification. *IEEE Trans. Pattern Anal. Mach. Intell.* 25 (2003), 1505–1518.
[52] Xueyi Wang, Joshua Ellul, and G. Azzopardi. 2020. Elderly Fall Detection Systems: A Literature Survey. *Frontiers in Robotics and AI* 7 (2020).
[53] Xueyi Wang, Joshua Ellul, and G. Azzopardi. 2020. Elderly Fall Detection Systems: A Literature Survey. *Frontiers in Robotics and AI* 7 (2020).
[54] Daniel Joseph Warrington, Elizabeth Shortis, and Paula Jane Whittaker. 2021. Are wearable devices effective for preventing and detecting falls: an umbrella review (a review of systematic reviews). *BMC Public Health* 21 (2021).
[55] Jun Wu, Ke Wang, Baoping Cheng, Ruifeng Li, Changfan Chen, and Tianxiang Zhou. 2019. Skeleton Based Fall Detection with Convolutional Neural Network. *2019 Chinese Control And Decision Conference (CCDC)* (2019), 5266–5271.
[56] Tong Xiao, Shuang Li, Bochao Wang, Liang Lin, and Xiaogang Wang. 2017. Joint Detection and Identification Feature Learning for Person Search. *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (2017), 3376–3385.
[57] Tao Xu, Yun Zhou, and Jing Zhu. 2018. New Advances and Challenges of Fall Detection Systems: A Survey. *Applied Sciences* 8 (2018), 418.
[58] Tao Xu, Yun Zhou, and Jing Zhu. 2018. New Advances and Challenges of Fall Detection Systems: A Survey. *Applied Sciences* 8 (2018), 418.
[59] Sijie Yan, Yuanjun Xiong, and Dahua Lin. 2018. Spatial Temporal Graph Convolutional Networks for Skeleton-Based Action Recognition. *ArXiv* abs/1801.07455 (2018).
[60] Huiyu Zhou and Huosheng Hu. 2008. Human motion tracking for rehabilitation - A survey. *Biomed. Signal Process. Control.* 3 (2008), 1–18.