# Human Movement Detection using Attitude and Heading Reference System

George K. Fourlas
Technological Educational Institute
of Central Greece (Lamia)
3rd km of Old National Road
Lamia-Athens, PC 35100
+30 22310 60186
gfourlas@teiste.gr

Ilias Maglogiannis
University of Piraeus
80, Karaoli and Dimitriou Str
Piraeus, PC 18534
+30 210 4142517
imaglo@unipi.gr

## ABSTRACT
Among different types of human movement, falls are the most important since they related with high social and economic costs. Falls can cause various unintentional injuries such as fractures or in the worst-case scenario even lead to death, elderly citizen. Wearable devices present a growing interest in health care applications since they can detect signals of human activity and continuously monitoring critical parameters, offering a reliable and inexpensive solution. In this paper, an attitude and heading reference system - inertial measurement unit (IMU) is used in order to detect human movement and especially different type of falls.

## Categories and Subject Descriptors
J.3 [**Life and Medical Sciences**]: Medical information systems – *sensors, healthcare monitoring*

## General Terms
Measurement, Performance, Experimentation, Security, Human Factors.

## Keywords
Fall Detection, Sensors, Healthcare Applications.

## 1. INTRODUCTION AND RELATED WORK
Human movement detection is one of the biggest challenges in healthcare applications. Kinesis problems affect lots of people especially elderly citizens. Among different types of human behavior, falls are the most important since they related with high social and economic costs [1]. Falls can cause various unintentional injuries such as fractures or in the worst case scenario even lead to death elderly, citizen. In the health insurance systems it absorbs a significant part of social resource. Falls in in elderly residents are estimated to affect 30% of those over 65 on an annual basis. Even though most falls doesn't cause injury, between 5-10% of elderly people who fall each year sustain serious injury, such as fracture, head trauma, serious concussion and hospitalization. Of the estimated 1% of the elderly who fall and sustain a hip fracture, 20-30% dies within one year of the fracture. Almost two thirds of elderly population with hip fracture never regains their pre-fracture activity status and one-third needed admission to nursing home [2]. The cost forecasting of medical care of elderly people regarding falls injuries goes to $43.8 billion by 2020 [3]-[4].

Undoubtedly the study and development of systems for fall detection is challenging and presents enormous interest. Many approaches have been proposed [5]-[11]. According to [12] fall detection systems are based in three types of equipment: wearable devices, ambient devices and camera-based devices.

Several works exist in literature dealing with the wireless monitoring of patients or elderly. In [13] and [14] authors present reviews concerning wireless sensor networks for healthcare and body sensor networks as well as related applications and addresses some of the challenges and implementation issues. In [15] a WSN for rehabilitation supervision with a focus on key scientific and technical challenges that have been solved as well as interdisciplinary challenges that are still open is presented. In the work of [16] the research interest is focused on describing the implementation and the evaluation of a wireless body sensor system that monitors human physiological data at home. Authors present a waist-mounted tri-axial accelerometer unit to record human movements.

There also exist a number of works [17] – [22] utilizing movement sensors, especially tri-axial MEMS accelerometer. MEMS accelerometers through wireless networks enabled the realization of wearable monitoring systems, capable of recording the movement of an individual.

In this paper, an attitude and heading reference system is used in order to detect human movement and especially falls. Moreover, the proposed system promises much more for investigating and developing a complete health care system based on a wearable devices with high adaptation to physician, physiotherapist and patient needs.

The rest of the paper is organized as follows. The proposed system is presented in Section 2. In section 3 the experimental results of the proposed system are presented. Conclusions and directions for future work are presented in Section 4.

## 2. THE PROPOSED SYSTEM

As mentioned above, the main goal of the proposed methodology is to detect human movement and especially falls. For this purpose an inertial measurement unit (IMU) is used, that is capable to achieve acceleration and orientation sensing.

The experimental system consists mainly of the IMU that collects the body measurements, acceleration and orientation, and transmits the corresponding data to a computer for real time monitoring (Fig. 1).

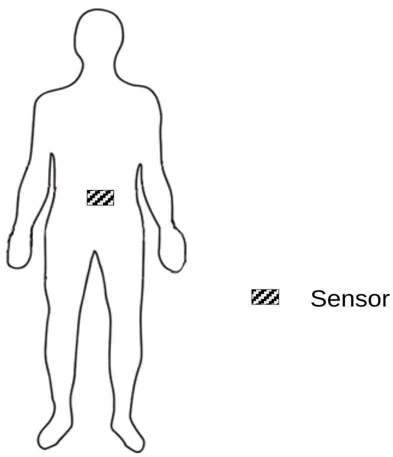


**Figure 1. System overview.**

### 2.1 Sensor system

As already mentioned the monitoring of human movement can be easily achieved using accelerometers. Usually accelerometers are parts of inertial measurement units, (IMUs), which are used for orientation and they consist of accelerometers, gyroscopes and magnetometers. These types of sensors are relatively low cost devices that can achieve good dynamic specification and can easily be integrated in a wearable system. In this work the Xsens MTi-30 AHRS is used (Fig. 2).


**Figure 2. Coordinate system of the encased MTi.**

The MTi-30 AHRS is a full gyro-enhanced attitude and heading reference system (AHRS). It outputs drift-free roll, pitch and true/magnetic north referenced yaw, plus sensors data: 3D acceleration, 3D rate of turn and 3D earth-magnetic field data.

The sensor coordination system is a right-handed Cartesian system that is body-fixed to the device and is used to output rate-of-turn, acceleration and magnetic field. The encased version of the MTi shows the coordination system on the sticker.

Figure 2 depicts the sensor coordinate system on the encased MTi and Figure 3 below displays the OEM version.

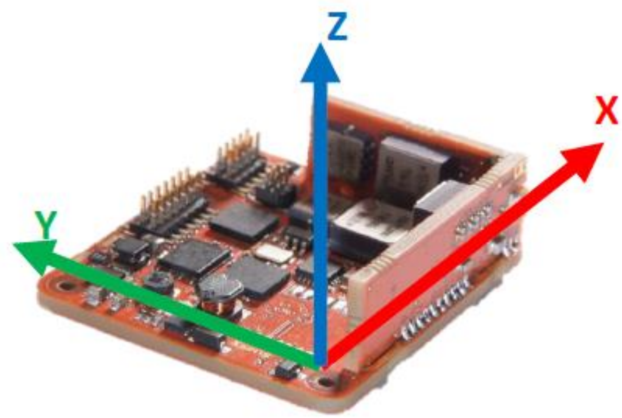


**Figure 3. Coordinate system of the MTi-OEM.**

Table 1 shows the system specifications concerning the gyroscope, the accelerometer and the magnetometer.

**Table 1. System specifications**

| | Gyroscope | | Accelerometer | | Magnetomete | |
|---|---|---|---|---|---|---|
| | Typ | Max | Typ | Max | Typ | Max |
| Standard full range | 450º/s | - | 50m/s² | - | | +/- 80 µT |
| Bias repeatability (1 yr) | 0.2º/s | 0.5o/s | 0.03m/s² | 0.05m/s² | | |
| In-run bias stability | 18º/h | | 40 µg | | | |
| Bandwidth (-3 dB) | 415 Hz | N/A | 375 Hz | N/A | | |
| Noise density | 0.03º/s/√Hz | 0.05º/s/√Hz | 80 µg/√Hz | 150 µg/√Hz | 200 µG/√Hz | |
| g-sensitivity (calibrated) | 0.006º/s/g | 0.02º/s/g | N/A | N/A | | |
| Non-orthogonality | 0.05 deg | - | 0.05 deg | - | | |
| Non-linearity | 0.03% FS | 0.1% FS | 0.03% FS | 0.5% FS | 0.1% FS | |

## 2.2 Visualization software

The inertial measurement unit collects data, which are transmitted through the USB port and the corresponding graphs are displayed on a computer. The computer runs the Xsens' MT Manager visualization software environment.

The MT Manager software allows to:

- view 3D orientation in real-time
- view inertial and magnetic sensor data in real time
- view latitude, longitude, altitude plots in real time
- export log files to other formats like ASCII
- change and view various device settings and properties
- run a self-test to check the mechanical functions of the inertial sensors and magnetometer.

Figure 4 illustrates a screenshot of sensor data representation within MT Manager, containing three main frames of the 3D calibrated measurement data vs. time:

- acceleration (from the accelerometers) in $m/s^2$
- angular velocity (from the gyroscopes) in deg/s
- magnetic field (from the magnetometers).

The line colours are assigned as follows:

- Red: acceleration, angular velocity (roll) and normalised magnetic field in X direction
- Green: acceleration, angular velocity (pitch) and normalised magnetic field in Y direction
- Blue: acceleration, angular velocity (yaw) and normalised magnetic field in Z direction

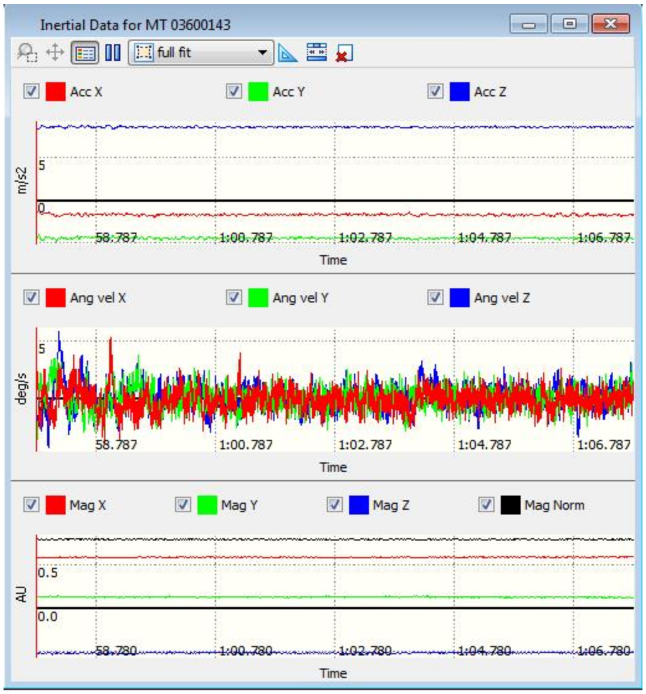


**Figure 4. Inertial and magnetic sensor data in real time.**

Figure 5 depicts the 3D Box View which is a real-time graphical representation of the MT orientation measurements, i.e. roll, pitch and yaw.

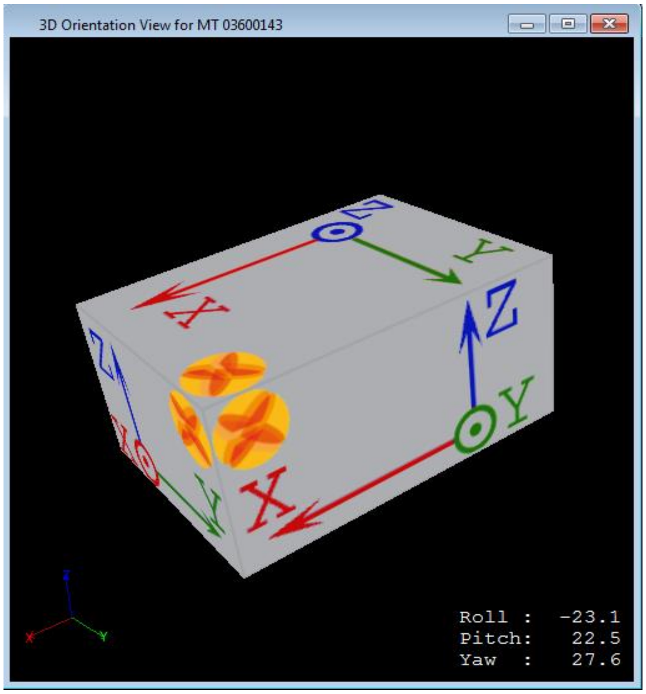


**Figure 5. 3D orientation in real-time.**

## 3. EXPERIMENTAL RESULTS

The aforementioned system has been tested for fall detection in different type of human movements. The IMU device was placed with an elastic band on the chest (Fig. 6.).

**Figure 6. Wearable sensor on the chest.**

During the experiment we examined the following movements, which were considered the most prominent:

- walking
- sitting on a chair
- backward falls
- forward fall
- right & left side lateral fall

The visualized experimental results are presented in the Figures below. More specifically, Figures 7, 9, 11, 13, 15 and 17 depict inertial and magnetic sensor data in real time for the above-mentioned human movements.

Figures 8, 10, 12, 14, 16 and 18 show orientation based on IMU measurements during the six different types of movements.

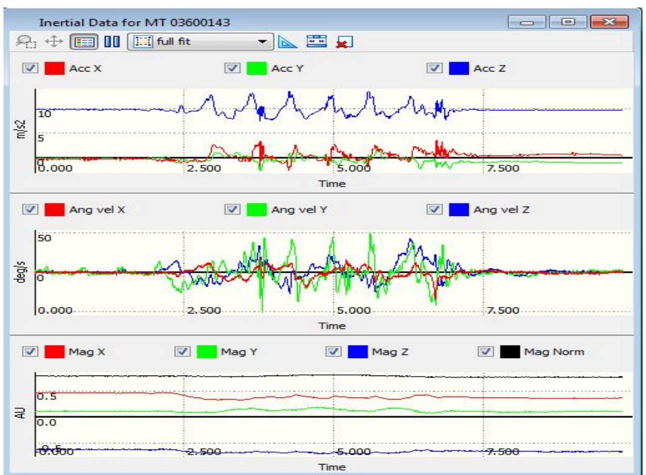


**Figure 7. Inertial and magnetic sensor data in real time during walking.**


**Figure 8. Orientation sensor data in real time during walking.**


**Figure 9. Inertial and magnetic sensor data in real time during sitting on a chair.**


**Figure 10. Orientation sensor data in real time during sitting on a chair.**

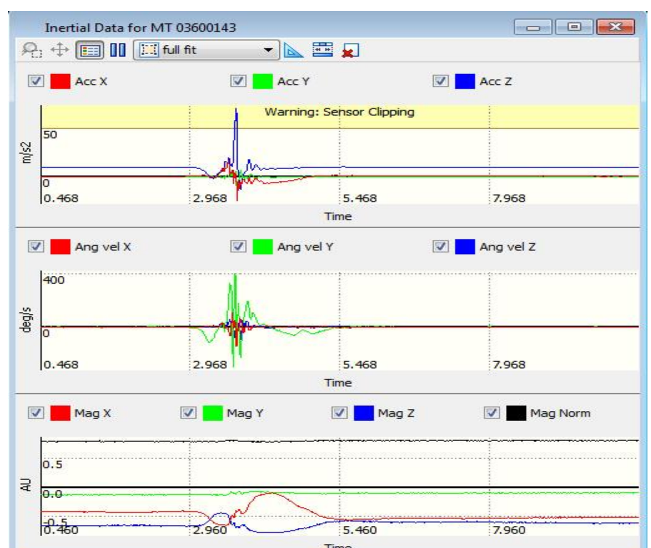


**Figure 11. Inertial and magnetic sensor data in real time during backward falls.**


**Figure 12. Orientation sensor data in real time during backward falls.**

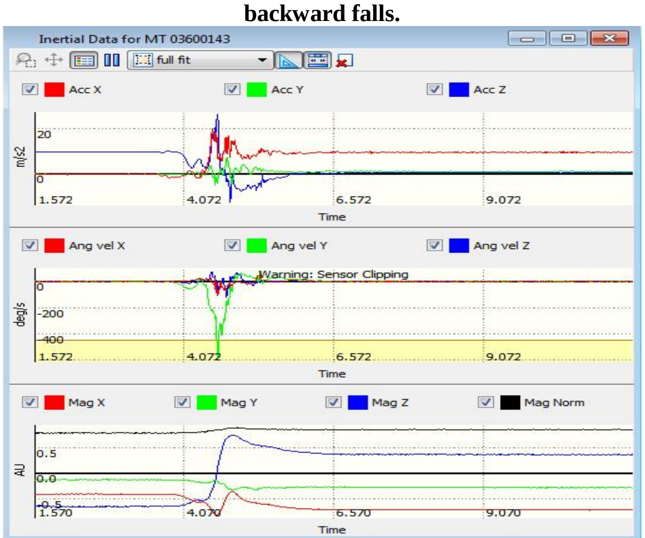


**Figure 13. Inertial and magnetic sensor data in real time during forward fall.**


**Figure 14. Orientation sensor data in real time during forward fall.**


**Figure 15. Inertial and magnetic sensor data in real time during right side lateral fall.**


**Figure 16. Orientation sensor data in real time during right side lateral fall.**

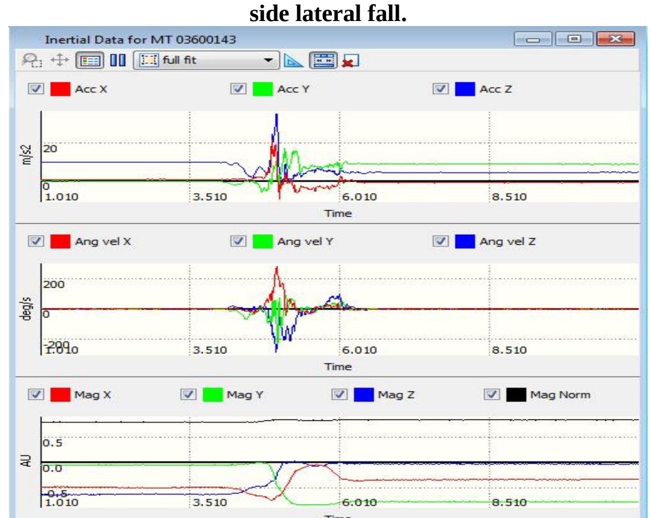


**Figure 17. Inertial and magnetic sensor data in real time during left side lateral fall.**


**Figure 18. Orientation sensor data in real time during left side lateral fall.**

The above experimental results have proven the feasibility of the implemented system to distinguish between the various types of movement and its ability to detect falls. Proper signal processing (i.e. Kalman filtering) can be used for eliminating noise. The next step is to use a real time decision module to detect the falls. Such an algorithm is the cumulative sum (CUSUM) algorithm proposed by the authors in [23], which is proven quite efficient for prompting fall detection in real-time. In a future work we intend to combine data of additional sensors (e.g. biosignals, audio, etc.) with data mining techniques and change detections algorithms to further improve the accuracy of the system and add additional functionalities, such as fall severity estimation.

## 4. CONCLUSION

An attitude and heading reference system - IMU in order to detect human movement and especially different type of falls has been presented in this paper. The study and implementation of the proposed system have multiple goals such as the investigation of building a wearable system for healthcare applications enabling independent living.

Current research includes the extension of the proposed of system for wireless communication. An important issue under investigation is the development of a whole healthcare system to meet the requirements of physician and patient needs.


## 5. ACKNOWLEDGMENTS

This research is implemented through the Operational Program "Education and Lifelong Learning" and is co-financed by the European Union (European Social Fund) and Greek national funds. The work is part of the research project entitled «STHENOS» of the Act "THALIS".


## 6. REFERENCES


[1] Chia-Chi Wang, Chih-Yen Chiang, Po-Yen Lin, Yi-Chieh Chou, I-Ting Kuo, Chih-Ning Huang, and Chia-Tai Chan. Development of a fall detecting system for the elderly residents. In Bioinformatics and Biomedical Engineering, 2008. ICBBE 2008. The 2nd International Conference on, 2008.

[2] K. Khoshhal, H. Aliakbarpour, J. Quintas, P. Drews, J. Dias - Probabilistic LMA-based Classification of Human Behaviour Understanding Using Power Spectrum Technique – Fusion 2010 - 13th International Conference on Information Fusion - EICC Edinburgh, UK, July 26-29 2010

[3] K. Brewer, C. Ciolek, M. F. Delaune, “Falls in community dwelling older adults: Introduction to the problem,” APTA Continuing Education Series, pp. 38–46, July 2007.

[4] Changhua Healthcare Quality, http://www.qi.org.tw/.

[5] U. Lindemann, A. Hock, M. Stuber, “Evaluation of a fall detector based on accelerometers: a pilot study,” Medical & Biological Engineering & Computing, vol. 43, pp. 1146–1154, 2005.

[6] N. Noury, P. Rumeau, A. K. Bourke, G. ´ OLaighin, and J. E. Lundy, “A proposal for the classification and evaluation of fall detectors,” IRBM, vol. 29, no. 6, pp. 340–349, 2008.

[7] M. C. Chung, K. J.McKee, C. Austin et al., Posttraumatic stress disorder in older people after a fall,” International Journal of Geriatric Psychiatry, vol. 24, no. 9, pp. 955–964, 2009.

[8] S. Sadigh, A. Reimers, R. Andersson, and L. Laflamme, “Falls and fall-related injuries among the elderly: a survey of residential-care facilities in a Swedish municipality,” Journal of Community Health, vol. 29, no. 2, pp. 129–140, 2004.

[9] A. Shumway-Cook, A. M. Ciol, J. Hoffman, J. B. Dudgeon, K. Yorkston, and L. Chan, “Falls in the medicare population: incidence, associated factors, and on healthCare,” Physical Therapy, vol. 89, no. 4, pp. 324–332, 2009.

[10] S. Elliott, J. Painter, and S. Hudson, “Living alone and fall risk factors in community-dwelling middle age and older adults,” Journal of Community Health, vol. 34, no. 4, pp. 301–310, 2009.

[11] X. Yu, “Approaches and principles of fall detection for elderly and patient,” in Proceedings of the 10th IEEE International Conference on E-Health Networking, Applications and Service (HEALTHCOM ’08), pp. 42–47, Singapore, July 2008.

[12] Gabriele Rescio, Alessandro Leone, and Pietro Siciliano. 2013. Supervised Expert System for Wearable MEMS Accelerometer-Based Fall Detector. *Journal of Sensors* Volume 2013.

[13] Jeong Gil Ko, Chenyang Lu, Srivastava, M.B., Stankovic, J.A., Terzis, A., Welsh, M. 2010. Wireless Sensor Networks for Healthcare. *Proceedings of the IEEE*, Vol. 98, Issue: 11, pp 1947 – 1960.

[14] C. Liolios, C. Doukas, G. Fourlas, I. Maglogiannis, 2010. An Overview of Body Sensor Networks in Enabling Pervasive Healthcare and Assistive Environments. *3rd International Conference on Pervasive Technologies Related to Assistive Environments (PETRA'10)*, Samos, Greece, June 23-25.

[15] Abdelkrim Hadjidja, Marion Souila, Abdelmadjid Bouabdallaha, Yacine Challala, Henry Owen. 2013. Wireless Sensor Networks for Rehabilitation Applications: Challenges and Opportunities. *Journal of Network and Computer Applications* 36 (2013) 1-15.

[16] Chao Chen, Carlos Pomalaza-Raez. 2010. Implementing and Evaluating a Wireless Body Sensor System for Automated

Physiological Data Acquisition at Home. International *Journal of Computer Science and Information Technology* 2.3 (2010), pp24-38.

[17] Tadej Beravs, Janez Podobnik, Marko Munih. 2012. Three-Axial Accelerometer Calibration Using Kalman Filter Covariance Matrix for Online Estimation of Optimal Sensor Orientation. *IEEE Transactions on Instrumentation and Measurement,* 61(9), pp. 2501 – 2511.

[18] Ronit Slyper and Jessica K. Hodgins. 2008. Action Capture with Accelerometers. *Proceedings of the 2008 ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, pp. 193-199.

[19] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, B. G. Celler. 2006. Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring. *IEEE Transactions on Information Technology in Biomedicine*, vol. 10, no. 1, pp. 156–167.

[20] G. Anania, A. Tognetti, N. Carbonaro et al. 2008. Development of a novel algorithm for human fall detection using wearable sensors. *Proceedings of the IEEE Sensors (SENSORS '08), pp. 1336–1339, Lecce, Italy*, October 2008.

[21] A. K. Bourke, P. van de Ven, M. Gamble et al. 2010. "Evaluation of waist-mounted tri-axial accelerometer based fall-detection algorithms during scripted and continuous unscripted activities. *Journal of Biomechanics*, vol. 43, no. 15, pp. 3051–3057.

[22] F. Bagala, C. Becker, A. Cappello et al. 2012. Evaluation of accelerometer-based fall detection algorithms on real-world falls. *PLoS One*, vol. 7, Article IDe3706.

[23] S.K. Tasoulis, C.N. Doukas, V.P. Plagianakos, I. Maglogiannis, Statistical data mining of streaming motion data for activity and fall recognition in assistive environments, Neurocomputing, Volume 107, 1 May 2013, Pages 87-96.