Exploring Accelerometer-based Step Detection by using a Wheeled Walking Frame

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ABSTRACT

Step detection with accelerometers is a very common feature that smart wearables already include. However, when using a wheeled walking frame / rollator, current algorithms may be of limited use, since a different type of motion is being excreted. In this paper, we uncover these limitations of current wearables by a pilot study. Furthermore, we investigated an accelerometer-based step detection for using a wheeled walking frame, when mounting an accelerometer to the frame and at the user's wrist. Our findings include knowledge on signal propagation of each axis, knowledge on the required sensor quality and knowledge on the impact of different surfaces and floor types. In conclusion, we outline a new step detection algorithm based on accelerometer input data. Our algorithm can significantly empower future off-the-shelf wearables with the capability to sufficiently detect steps with elderly people using a wheeled walking frame. This can help to evaluate the state of health with regard to the human behavior and motor system and even to determine the progress of certain diseases.

CCS CONCEPTS

• **Human-centered computing → Accessibility technologies**; • Human-centered computing. → Ubiquitous and mobile computing systems and tools.

KEYWORDS

Wheeled Walking Frame; Step Detection; Step Counting; Smartwatch; Spatial User Input; Rollator; Elderly People.

1 INTRODUCTION

Counting steps throughout the day is an important factor to infer on the user's activity level. Knowing about the activity level can especially be important for elderly people, such as to improve the dosage of medication or to indicate health and disease conditions [14]. While smart wearables are on the rise, they become socially acceptable and also more powerful in terms of sensing technology and battery power [20]. Recently, wrist-worn devices such as smartwatches are being increasingly deployed for elderly people [1][2][10][16][17][18] in order to track their vital data, such as their activity level, which is based on step counting [4][22]. However, step counting algorithms are prone to fail when using a rollator. Hereby, the users are holding themselves tightly to an object, which significantly reduces motion signal. In addition, the usage of walking frame influences the walking style and gait. These circumstances are to be considered in an adapted step detection algorithm for using rollators.

In this paper, we introduce an accelerometer-based step detection and evidence a difference walking behavior while using a rollator with a pilot study using 8 state-of-the-art wearables. We present three studies investigating particularities of accelerometer-based step detection by using a wheeled walking frame. Furthermore, we explain how an accelerometer-based step detection usually works and discover occurring challenges with previous and current implementations. Hence, we contribute with:

- a brief evaluation of current step detections on state-of-the-art wearables to motivate our work,
- an investigation on accelerometer-based step detection when using a wheeled walking frame and thus knowledge on the spreading of signal on different axis, knowledge on the required sensor quality and knowledge on the impact of different floor types
- an outline of an improved step detection algorithm, which is based on a three axis-accelerometer, and an outlook on how this can be useful for elderly people in future, such as for an everyday assessment

2 RELATED WORK

2.1 Accelerometer-based Step Detection

Since last century, pedometers were introduced, which are mechanical step counters. These devices consist of a swinging pendulum to count steps and display the count with a clock- like pointer. The mechanical pedometers were mounted at the hip and provided an astonishing recgonition of about ~90% with a steady walk [13]. Electromechanical pedometers improved long-term reliability and accuracy [25]. Early applications aimed to improve outdoor and indoor navigation [24]. By the increase of calculation capabilities of the sensor itself, some of the acceleration sensors already include step counters implemented on a hardware level. Wearable devices, such as smart phones or smart watches, archive step information already on operating system level. The general concept of an accelerometer-based step detection is described in [25]. Hereby, we require specific body movements and a

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computational device with sensors, attached to the user`s body. As a matter of fact, when making steps, we swing our hip and arms [6] and therefore our wrists receives the motion as well. Mounting the sensor at the wrist can detect changes in acceleration and transmit the data to a computing device, which has algorithm running to calculate the number of steps taken in a certain time span [21]. Independent from the individual implementation of step detection algorithms, most algorithms use a very similar recognition chain when computing accelerometer data of a wrist-mounted devices. The very first step is usually a segmentation process, which chops raw data streams into windows of individual sizes. Subsequently, filter stages remove unwanted noise, such as artifacts. The next step includes selecting the signal with the most characteristic motions, either a certain axis that shows the highest signal amplitude or a combination of suitable axes. To enable the detection of individual steps, a fixed or adaptive threshold is usually set. The last stage includes counting of maxima that exceeded the pre-defined threshold. Since the accuracy of such a step detection can vary and is depended on different factors, such as window size, sensor resolution, noise reduction etc. it is beneficial to individually tweak a configuration based on the sensor device and context.

2.2 Challenges with Wrist-Mounted IMUs

A few problems can occur by using wrist-mounted peripherals, such as wearables with accelerometers, for a step detection. For instance, many movements do not have reoccurring signals, which makes it very unlikely to detect steps correctly (movement or motion noise). These problems have also been looked into by Clarke et al. [5], who investigated four measurement positions (ankle, thigh, wrist, and waist). While different sensor positions [9] at the body can have considerable influence on step recognition, especially speed levels are significantly affecting the results [7]. These inaccuracies are in particular very well known for common step detections with accelerometers [8] when grasping an object and holding onto it, such as a wheeled walking frame. This usually results in a variety of different acceleration signals, which has been confirmed in previous studies.

Therefore, Ballesteros et al. [3] and Martins et al. [11], both investigated on applying different types of sensors directly to walking frame in order to better detect steps. Still, it has been shown that multiple errors remain when attempting to accurately detecting movement-based detections, such as steps. To make an accurate everyday assessment it only makes sense to expand upon the amount of different movement signals to lower the amount of unknown execution patterns (motion noise) in the data. A step detection in a walking aided scenario (e.g. with walker frame or rollator) is a very specific solution to such a problem, but an important one nonetheless. Because of the individual execution style, with whom an impaired patient performs walking with a frame or rollator, the usual wrist motion is no longer applicable. The hands of a patient are firmly grasping the handles of the device and the characteristic forward backward movement applied in many step detection algorithms is no longer recognizable. More importantly, the motion and impact caused by the feet touching the ground is performed much slower and lighter in case of elderlies using a rollator.

3 PILOT STUDY: CURRENT IMPLEMENTATIONS

In this pilot study, we wanted to find out how well current smartwatch step detection implementations work. Therefore, we tested eight state-of-the-art wrist-worn smart wearables on a healthy subject (30yrs, 183cm, 83kg) who was using a wheeled walking frame. With each smart wearable (see *Figure 1*) the subject walked twice ~150 steps.

Figure 1. Eight wrist-worn wearables were tested for counting steps, which were: No1 D5, No1 D5+, LG Round R, Sony Smartwatch 3, Samsung Gear S, Fitbit Wristband, Apple Watch 1, and the Garmin VivoFit 3 Wristband.

Although the results (*see Figure 2*) are only based on two trials with a single subject, substantial different recognition rates are not expected with broader sample sizes.

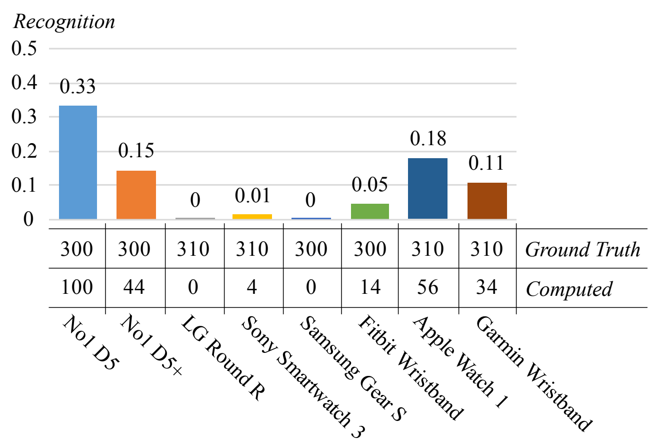

Figure 2. With an average recognition (recall rate) of *M*=10.35% *SD*=11.5% all devices apparently underperformed due to the marginal wrist motion.

The results are apparently revealing that none of the tested wearables is able to correctly detect steps taken when using a rollator. Therefore, using this data for any health or activity tracking apps would result in invalid conclusions. This can be crucial for an elderly person, whose medication may rely on this information.

4 INVESTIGATING ACCELEROMETER-BASED STEP DETECTION BY USING A ROLLATOR

In order to investigate the affordances of a step detection of wrist-worn devices while using a walking frame, we conducted three experiments. The outcomes of these studies are considered for the creation of a more stable algorithm, which is also briefly introduced in this paper.

4.1 Study Setup

As an apparatus, we used an ordinary wheeled walking frame (*see Figure 3*), which we attached with a Shimmer3 [19] sensor, which incorporates a high resolution accelerometer.

Figure 3. Displaying the apparatus; a rollator attached with a Shimmer3 IMU.

Then, the user was equipped with a Shimmer3 sensor device wearing it at his wrist. To evidence that a wrist-worn accelerometer-based step detection for a rollator would also work with an off-the-shelf smartwatch, which usually incorporates a low-resolution accelerometer, the user additionally had to wear an Android No.1 D5+ smartwatch (*see Figure 4*). Both devices dump accelerometer data into a CSV file, which we use for post-processing. While the smartwatch accelerometer only enables for 10bit resolution and 50Hz sampling rate, data from the Shimmer3 IMU was recorded at 12bit resolution with 100Hz.

In terms of execution style, the user was having both hands firmly grasping the designated walking frame handles like an elderly person would do.

4.2 Study1: Determining Suitable Axes

The first preliminary study we conducted, included checking which axis provides a stable reoccurring signal in a walking aided scenario. Furthermore, we wanted to investigate on the amplitude and noise the signal of an accelerometer would receive.

Therefore, we attached an acceleration sensor, along the axis of direction of motion of the walker itself. We mounted a Shimmer3 [19] sensor device to the walking frame as illustrated in *Figure 3*. This spot was selected due to the importance of having a fixed position at the walking frame, which is resistant to being bend or possibly twisted while using it. This was done to lower the amount of data distortions that are prone to happen on a walking frame. The artifacts that were created by the spinning wheels and other moving parts.

With three users we walked slowly through the room (indoor). The number of steps performed was predefined. The time span and the traversed space were both not of any concern in this study yet. We were able to identify the forward-backward movement axis as well as the left-right movement axis as suitable for providing reoccurring step related information. The dominance of either of the axes depends on the execution of the specific walking style. This means, a very slow but steady movement has a stronger amplitude in the forward-backward axis, while a rather twisting motion (due to leaning on the walking frame) usually shows bigger amplitudes is the left-right axis. The signal itself was steady and the artifacts due to moving parts where filtered.

In summary, we identified the need of fusing multiple axes in order to cope with different execution styles. This result is underlined by the fact that characteristic reoccurring motions in a walking aided scenario (e.g., walking frame) can be spread on multiple axes or may switch in orientation due to changing execution style throughout the day. Compared with standard walking or step detection techniques in non-aided walking scenarios, this behavior may be contrary.

4.3 Study 2: Signal Quality of Consumer Electronics

The second preliminary study, we conducted, was to test whether we can detect similar signals gathered from the Shimmer3 IMU in comparison to standard consumer electronics, such as devices like an off-the-shelf- Android smartwatch. To evaluate the differences of signal quality, the attached two wrist-worn sensor devices to the user *(see Figure 4)*. Then, we repeated the walking test similar to our first study. The results of the second study showed that a

Figure 4. Shimmer3 IMU and an Android No.1 D5+ is worn at the wrist.

signal difference is visible, but sufficient enough to determine axes-orientation, albeit we found a slightly different distribution of gravitational forces due to the hardware position and quality differences of the accelerometer. Also, the reoccurring signal, stemming from steps, can be found in the upwards-downwards axis, but with a low amplitude. This effect is caused by the approaching and detaching motions with respect to the rollator, which involve a twisting of the wrists.

4.4 Study3: Impact of Floor Types

The third preliminary study was conducted in order to evaluate the influence of the different types of floors with regard to signal amplitudes and steadiness.

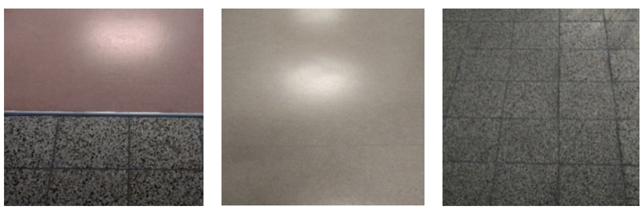

Figure 5. We encountered different floors to provide different signals. We evaluated: 1) doorstep, 2) linoleum, and 3) flagstone

We evaluated different floor types and checked whether detection issues may be caused by variations of floor type, or if we could simply ignore them. Therefore, we recorded two test sets in order to evaluate that influence. For the first test set, we used a rollator to walk on a straight hallway with different types of floor: smooth linoleum, and flagstone. Both floor types were separated by a doorstep (*see Figure 5*). Similar to the second pilot study, we attached a Shimmer3 IMU to the users' wrist and collected the raw sensor acceleration data from five users.

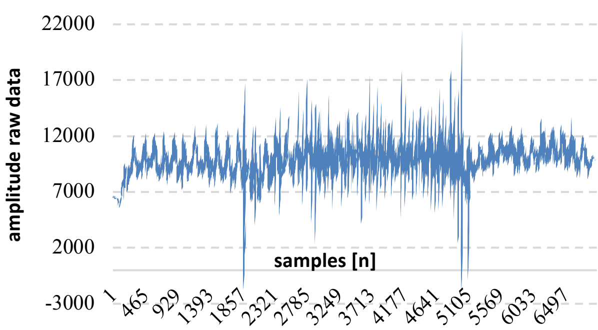

Figure 6. Showing raw data of the x-axis from a single user.

Figure 6 shows the raw acceleration data of the x-axis of the Shimmer3 IMU mounted at the right wrist. The average number of steps to the border between the two floors was 22 steps. The peak amplitude at about 1800 samples characterizes the moment when the rollator passes the metal doorstep. After the doorstep, the participant moved over the stone tiled floor for 40 steps (average of all participants) before returning to the smooth floor. There is an additional frequency accumulated on the signal when walking on the flagstone, which is caused by joints between the stone tiles.

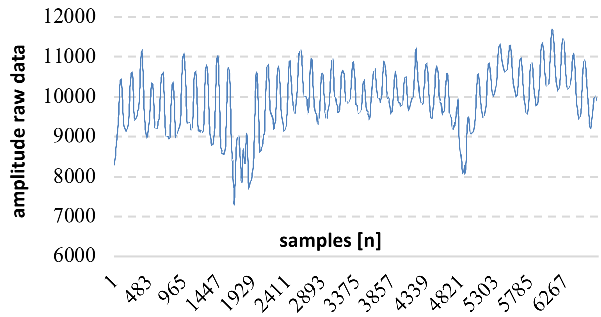

Figure 7. Showing filtered data of the x-axis.

To still see the steps performed, we must clear the signal by applying a filtering. *Figure 7* shows the x-axis of the same data set treated with a low-pass filtering. The change of floor type is still visible with two local minima. However, a made steps become visible now despite the frequency modulation, which may be caused by different floors.

In summary, the underground surface on which the walking frame is used does indeed have an impact on the sensor data and thus will most likely disrupt a normal step detection. The magnitude of the influence depends on the frequency range and amplitude of the underground-related noise (superposition), the walking frame itself (workmanship, tires), and the individual grip intensity. It is also to note that our test only included a continuous walking speed and step length. Vastly different undergrounds have not been tested. As pointed out in this short study, it is possible to deal with smaller underground differences. Moreover, the results indicate that changes in ground surface could also be detected.

5 IMPROVED STEP DETECTION ALGORITHM

As a result of our investigations, we developed an improved step detection algorithm (*see Figure 8*). Our algorithm is a straightforward activity recognition approach, which is based on an accelerometer.

We first segment the data with a window size of 1024. A pre-processing is undertaken with a detrend filtering and an offset filtering. We then create a 3d vector norm. Here, we need to consider that one axis must be inverted, to avoid a canceling out of data [15]. A butterworth bandpass filter with a lower cutoff freq. of 0.25 Hz and an upper cutoff freq. of 1.08 Hz showed best results. Then, a peak detection can be applied. The counted maxima need to be multiplied by two, because each maxima swing of the arm represents two steps. A more detailed description of our algorithms and an evaluation is being presented by Matthies et al. [12].

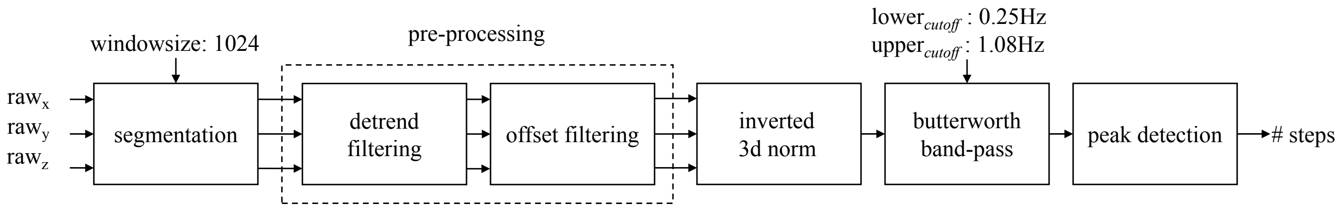

Figure 8. **We propose an improved algorithm for an accelerometer-based step detection algorithm.**

5.1 Outlook

By extracting step parameters from the algorithm, an assessment of the current state of health with regard to the human motor system or even progressing diseases [23] (e.g. Parkinson, Multiple Sclerosis [19], Dementia [4]), could be achieved. Parameters of relevance for an everyday assessment with the involvement of walking frames include:

- steps walked with and without a walking frame
- quotient of activity to non-activity
- the steadiness of a performed step frequency
- the longest continuous walk (daily)
- walking speed with or without a walking frame
- distance walked in a certain timespan
- number & length of breaks throughout a walking set

These parameters can be potentially computed by applying our proposed algorithm. For instance, step frequency can be determined by number of steps in a defined timespan. These timespans can be compared to succeeding windows, which leads to a parameter for steadiness. Activity and non-activity quotient could be computed by determining the time spent walking and comparing it to the residual time. Moreover, the application of acceleration sensors enables for a computation of step velocity and distance walked. Therefore, acceleration in the direction heading to is integrated over the length of a step, which also implies step velocity. Step velocity over time leads to the distance traveled. In addition, windows of low motion amplitudes indicate breaks in walking activities.

6 CONCLUSION

In this paper, we investigated accelerometer-based step detection when the user is in need of a wheeled walking frame / rollator. We explained the rational principle of a step detection and their caveats. A pilot study revealed currently deployed algorithms to perform insufficiently. During our investigation, we mounted an accelerometer to the walking frame as well as the user's wrist. Our findings include knowledge on the spreading of signal on different axis, knowledge on the required sensor quality and knowledge on the impact of different floor types. In conclusion, we outline a new step detection algorithm based on accelerometer input data. More details and performances of our improved algorithm are published separately [12]. We believe our approach to significantly empower future off-the-shelf wearables with the capability to sufficiently detect steps with elderly people using a wheeled walking frame.

REFERENCES

[1] &gesund, mHealth Pioneers GmbH, Berlin, Germany, URL: https://und-gesund.de/en

[2] b-cared. Caregency GmbH. Vienna, Austria. URL: https://b-cared.com

[3] Ballesteros, J., Urdiales, C., Martinez, A. B., & van Dieën, J. H. (2016). On Gait Analysis Estimation Errors Using Force Sensors on a Smart Rollator. In *Sensors, 16(11)*, 1896. MDPI. DOI: http://doi.org/10.3390/s16111896

[4] Boletsis, C., McCallum, S., & Landmark, B. F. (2015). The use of smartwatches for health monitoring in home-based dementia care. In *International Conference on Human Aspects of IT for the Aged Population. 15-26.* Springer International Publishing. DOI: http://doi.org/10.1007/978-3-319-20913-5_2

[5] Clarke, C. L., Taylor, J., Crighton, L. J., Goodbrand, J. A., McMurdo, M. E., & Witham, M. D. (2016). Validation of the AX3 triaxial accelerometer in older functionally impaired people. In *Aging Clinical and Experimental Research*, 1-7. Springer International Publishing. DOI: http://doi.org/10.1007/s40520-016-0604-8

[6] Collins, S. H., Adamczyk, P. G., & Kuo, A. D. (2009). Dynamic arm swinging in human walking. In *Proceedings of the Royal Society of London B: Biological Sciences,* 276(1673), 3679-3688. DOI: http://doi.org/10.1098/rspb.2009.0664

[7] Ehrler, F., Weber, C., & Lovis, C. (2016). Influence of Pedometer Position on Pedometer Accuracy at Various Walking Speeds: A Comparative Study. In *Journal of Medical Internet Research*, 18(10), e268. JMIR Publications. DOI: http://doi.org/10.2196/jmir.5916

[8] Feng, Y., Wong, C. K., Janeja, V., Kuber, R., & Mentis, H. M. (2017). Comparison of tri-axial accelerometers step-count accuracy in slow walking conditions. In *Gait & Posture*, 53, 11-16. Elsevier. DOI: http://doi.org/10.1016/j.gaitpost.2016.12.014

[9] Floegel, T. A., Florez-Pregonero, A., Hekler, E. B., & Buman, M. P. (2016). Validation of Consumer-Based Hip and Wrist Activity Monitors in Older Adults with Varied Ambulatory Abilities. In *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, glw098. Oxford Academic. DOI: https://doi.org/10.1093/gerona/glw098

[10] Living Safely. Blackham, UK. URL: http://www.livingsafely.com

[11] Martins, M., Santos, C. P., Page, S., Saint-Bauzel, L., Pasqui, V., & Mézière, A. (2015). Real-time gait assessment with an active depth sensor placed in a walker. In *IEEE International Conference on Rehabilitation Robotics (ICORR).* 690-695. IEEE. DOI: http://doi.org/10.1109/ICORR.2015.7281281

[12] Matthies, D.J.C., Haescher, M., Nanayakkara, S., G. Bieber. (2018). Step Detection for Rollator Users with Smartwatches. In *Proceedings of the 6th Symposium on Spatial User Interaction (SUI'18).* ACM. DOI: https://doi.org/10.1145/3267782.3267784

[13] Melanson, E. L., Knoll, J. R., et. al. (2004). Commercially available pedometers: considerations for accurate step counting. In *Preventive medicine,* 39(2), 361-368. DOI: https://doi.org/10.1016/j.ypmed.2004.01.032

[14] Milenković, A., Otto, C., & Jovanov, E. (2006). Wireless sensor networks for personal health monitoring: Issues and an implementation. In *Computer communications*, 29(13), 2521-2533. Elsevier. DOI: http://doi.org/10.1016/j.comcom.2006.02.011

[15] Mortazavi, B. J., Pourhomayoun, M., Alsheikh, G., Alshurafa, N., Lee, S. I., & Sarrafzadeh, M. (2014). Determining the single best axis for exercise repetition recognition and counting on smartwatches. In *11th International Conference on Wearable and Implantable Body Sensor Networks.* 33-38. IEEE. DOI: http://doi.org/10.1109/BSN.2014.21

[16] Next Step Dynamics AB. Malmö, Sweden. URL: http://www.nextstepdynamics.com

[17] Revolutionary Tracker. USA. URL: http://www.revolutionarytracker.com

[18] Safe Link. Ottawa, USA.
URL: http://safelinkgps.com
[19] Schlesinger, S., Neuhaus, A., Thiele, A., Kippnich, M., Rashid, A., Griewing, B., & Daumer, M. (2011). Sind Mobilitätseinschränkungen bei Patienten mit Multipler Sklerose messbar? In *Klinische Neurophysiologie*, 42(01), 17-21. Thieme.
DOI: http://doi.org/10.1055/s-0031-1271750
[20] Shimmer (2016). Shimmer3 Wireless Sensor Platform (low noise acceleration sensor Kionix KXRB5-2042)
URL: https://tinyurl.com/shimmer3
[21] Susi, M., Renaudin, V., & Lachapelle, G. (2013). Motion mode recognition and step detection algorithms for mobile phone users. In *Sensors*, 13(2), 1539-1562. MDPI.
DOI: http://doi.org/10.3390/s130201539
[22] Trimpop, J., Schenk, H., Bieber, G., Lämmel, F., Burggraf, P. (2017). Smartwatch based Respiratory Rate and Breathing Pattern Recognition in an End-consumer Environment. In *Proceedings of the 4th International Workshop on Sensor-based Activity Recognition and Interaction in Rostock, Germany (iWOAR 2017).* ACM.
DOI: http://doi.org/10.1145/3134230.3134235
[23] Williams, K. L., Choy, N. L. L., & Brauer, S. G. (2016). Are Changes in Gait and Balance Across the Disease Step Rating Scale in Multiple Sclerosis Statistically Significant and Clinically Meaningful?. In Archives of physical medicine and rehabilitation, 97(9), 1502-1508. Elsevier.
DOI: http://doi.org/10.1016/j.apmr.2016.03.020
[24] Vildjiounaite, E., Malm, E. J., Kaartinen, J., & Alahuhta, P. (2002). Location estimation indoors by means of small computing power devices, accelerometers, magnetic sensors, and map knowledge. In *International Conference on Pervasive Computing (pp. 211-224).* Springer, Berlin, Heidelberg.
DOI: https://doi.org/10.1007/3-540-45866-2_17
[25] Weinberg, H. (2002). Using the ADXL202 in pedometer and personal navigation applications. *Analog Devices AN-602 application note,* 2(2), 1-6.