Age-Related Walkability Assessment: A Preliminary Study Based on the EMG

Francesca Gasparini[1(✉)], Alessandra Grossi[1], Katsuhiro Nishinari[2], and Stefania Bandini[1,2]

[1] Department of Computer Science, Systems and Communications, University of Milano, Bicocca, Italy
{francesca.gasparini,stefania.bandini}@unimib.it, a.grossi6@campus.unimib.it

[2] RCAST - Research Center for Advanced Science and Technology, The University of Tokyo, Tokyo, Japan
tknishi@mail.ecc.u-tokyo.ac.jp

Abstract. Populations around the world are rapidly ageing as the population aged 65 and over is growing faster than all other age groups. Most of the daily life actions of active elderly are related to walking activities, thus guaranteeing walking environments that are elderly-friendly are nowadays a priority to ensure healthy aging. Measuring and recognizing the affective state of people during walking activities contribute to a better comprehension of their perception of the environment, and a better definition of walkable urban area. With the aim of paving the way for assessing walkability, introducing quantitative evaluation tools, this work proposes to compare physiological responses of subjects of different ages, in different walking conditions. To this end a proper experiment has been designed in a controlled environment, considering both young adults and elderly, and adopting wearable devices. In this paper the analysis of the leg muscles activity acquired with Electromyography is presented. The results of this preliminary study highlight age-related differences in subjects facing both forced speed walks and collision avoidance tasks.

Keywords: Physiological signals · Active ageing · Walkability · Affective state · Collision avoidance · Electromyography

1 Introduction

In recent years, an increase of longevity in developed countries has been observed [2,10,17]. Growth of social welfare, education, medical care are only few of the possible reasons for this increase [11]. In a world where the number of elderly people is expected to growth even more, the creation of an environment suitable for active aging people is becoming a first priority problem [17]. In this situation, particular attention should be paid to walking activity. In fact most of the daily life activities of the elderly, such as sports, consumer life and social interactions, take place in the neighborhood and are mainly realized through walking

M. Baldoni and S. Bandini (Eds.): AIxIA 2020, LNAI 12414, pp. 423–438, 2021.
https://doi.org/10.1007/978-3-030-77091-4_25

activities [10]. Some studies underline that physical activity plays an important role in aging people's health as its practice allows to avoid physical or mental illnesses [13]. A walking environment that is elderly-friendly is thus a priority while planning the design of the cities of the future as well as to improve the existing ones [5]. Measuring if and to which extent an environment is comfortable and walkable for ageing people is the first step towards this direction [12]. One way to obtain quantitative measures of walkability is to assess safety perception while moving within an urban environment, in particular while walking, crossing and in general trying to avoid collisions. The assessment of safety perception can be performed with experiments and observations both through the design of the experimental setting in a protected space (*in-vitro* experiments) and/or with data collections in the real world setups (*in-vivo* experiments), relying on physiological responses, through the introduction of what can be defined affective walkability [1]. Physiological responses, can be considered honest indicators of our emotions and mood, and are nowadays widely adopted to recognize affective states [3]. Thanks to the development of the technology, several sensors can be easily integrated into smartphones or wearable devices [18], making them more comfortable and usable even in case of elderly people. So these signals could be valid indicators to assess quantitatively the safety perception of the elderly while interacting with the surrounding environment.

To this end, an experiment has been carried out in an indoor and controlled environment. Two different populations have been involved in the experiment: young adults and elderly people, in order to compare different perception of safe walk, varying the age. Different walking conditions have been also investigated, including dynamic collision avoidance. Physiological signals such as Plethysmogram (PPG) and Galvanic Skin Response (GSR) have been acquired using a wearable device. PPG and GSR are well indicated to detect emotional arousal, related to sensory alertness, mobility, and readiness to respond, activated in the interaction between subjects and the environment as a defensive reaction to preserve safety. Moreover, dealing with a dynamic interaction, motion data both physiological, measuring the muscle activity with Electromyogram (EMG) and inertial (accelerometer and gyroscope data) have been acquired.

The study presented in this paper focuses only on the analysis of the EMG physiological signals in order to reveal differences in pace and leg movements between young adults and elderly, trying to detect patterns that characterize their walking attitude in different walking environments. In Sect. 2, the experiment in a controlled environment performed to assess walkability is introduced. EMG signal processing is described in Sect. 3, while the results of the analysis of different walking conditions and the comparison of the behaviour of the two populations are detailed in Sect. 4. Finally conclusions and future works are reported.

Fig. 1. Wearable devices adopted.

2 Experimental Setup for Data Collection

A controlled experiment in a real laboratory environment at the University of Tokyo has been performed to collect data for studying walkability. Three within subject conditions (collision avoidance, forced speed walk and free walk) have been administered in one experimental session, performed by two experimental groups: a population of young adults, composed of 14 Japanese master and PhD students, (average age = 24.7 years, standard deviation = 3.3, 4 women), and Japanese elderly people (retired), 20 subjects,(average age of 65.15, standard deviation = 2.7, 10 women). During the whole experiment, physiological signals have been collected using wearable sensors produced by Shimmer[1]. Five main signals have been acquired: i) Galvanic Skin Response (GSR), connected to sweating and perspiration on the skin, ii) Photoplethysmography (PPG), that measures the blood volume registered just under the skin, which can be used to obtain the heart rate of the subject; iii) Electromyography (EMG), which measures the muscle activity of the person by surface sensors. In particular, activities related to the medial gastrocnemius muscle and to the anterior tibial muscle have been acquired using the same device; and iv) inertial data, trough Accelerometer and Gyroscope sensors. The adopted sensors are shown in Fig. 1.

The experiment lasted about 30 min and it was set up to acquire data from the subjects in different walking environments. The protocol of the experiment includes two tasks:

- **Collision avoidance:** two subjects at the same time walk with their own pace along the path depicted in Fig. 2, top left, clockwise and counterclockwise respectively. At about half of the path, they reach the collision avoidance zone where they have to avoid the collisions with both the obstacles (swinging pendulum) and the other subject. Then they complete the U path, with their natural pace and go back in the opposite direction repeating the same actions.

[1] https://www.shimmersensing.com/.

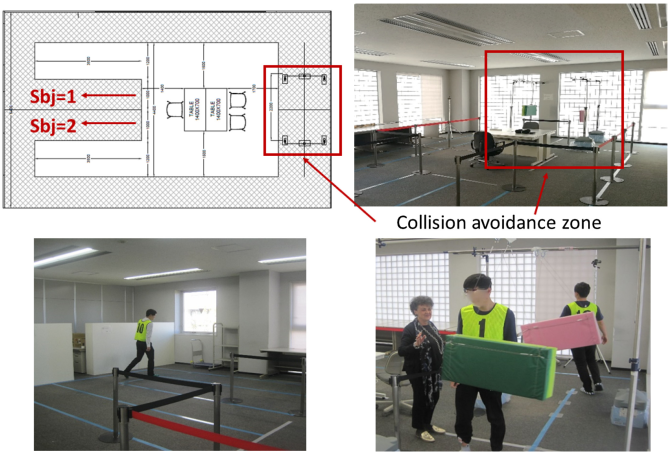


Fig. 2. Setting of the experiment. Top left: the plant of the indoor controlled environment, where a *U* path has been defined. The collision avoidance zone is identified by a red rectangle and depicted also in the image at the top right. The two obstacles are controlled by one of the experimenter and the two subjects have to avoid the collision (figure bottom right). During the rest of the *U* path, subjects walk with their own natural pace. (Color figure online)

– **Forced speed walk.** Participants walk with a forced speed based on the metronome ticking, along the same *U* path. Three speeds are considered: 70 bpm (*F1*), 85 bpm (*F2*) and 100 bpm (*F3*). This task lasts about 2 min. At the end, a questionnaire is provided to the participants to obtained information about the preferred walking frequency among those constrained by the metronome.

Only for the elderly there is a further task of **Free walk**, along the *U* path, back and forth, for about 40 s. In this task, participants can walk freely without obstacles or speed constraints.

All the tasks are separated by a period of resting time (**Baseline acquisition**) of about 1 min. The whole procedure is repeated three times.

GSR and PPG signals of all the subjects were collected, EMG signals were acquired only on a subset of participants. In particular, in the first experimental group EMG data were collected from 8 male subjects, while in the second group from 10 subjects including 3 females and 7 males.

3 EMG Data Analysis

The work here presented, focuses only on the analysis of the EMG signals. The two channel EMG have been acquired with a sampling frequency 512 Hz.

3.1 Subject Based Preprocessing

The two-channel EMG raw signals of each subject have been preprocessed by applying a denoising strategy based on the wavelet multi-resolution analysis

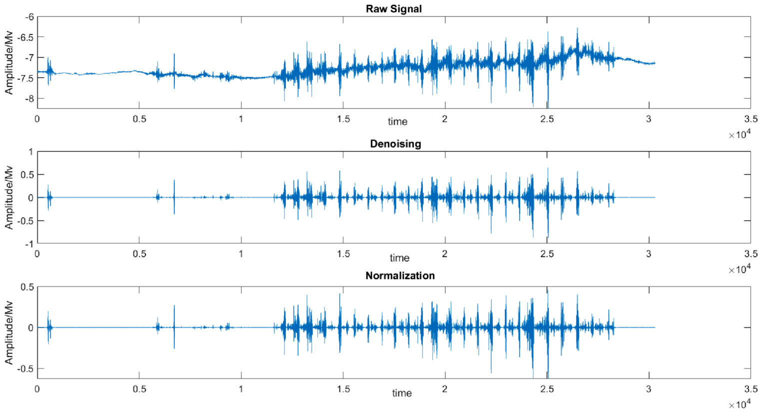


Fig. 3. Example of the applied preprocessing procedure on the EMG signal of a subject. Top image: the raw signal. Middle image: the results of the denoising procedure on the signal. Last image: Result of the normalization.

described in [16]. The signal is divided in frequency sub-bands using Maximal Overlap Discrete Transform (MODWT) with mother wavelet Daubeches-4 and with five levels of decomposition. To each sub-band, a Soft Thresholding is applied to the detail coefficients. The Universal Threshold calculated by the formula $t_k = \sqrt{2log(N_j))}$ was adopted, where N_j is the length of the j-th wavelet coefficient [4].

To compare signals of different individuals, permitting both inter and intra subjects analysis, the signals were normalized. Several different normalization strategies are reported in the literature, [6]. In this study each channel of the denoised EMG signals have been normalized dividing by the maximum peak activation level obtained from the signal under investigation. This value has been selected after an empirical study, because it has been observed to be able to decrease the variability between subjects. The normalization, as well as the denoising operation, have been applied to the whole signal of each subject, before segmenting the data into single tasks. An example of the preprocessing procedure on a subject's signal is showed in Fig. 3.

3.2 EMG Features Extraction

To compare different walking conditions and different behaviours of the two considered populations, two features have been extracted from the denoised and normalized EMG signals: walking frequency (known as Stride Frequency) and the mean power of the signal.

The first feature describes the number of steps performed by a subject per second and it is evaluated using a novel procedure described in this paper:

– **Task based pre-processing.** To further remove artifacts and noise, a task based denoising has been performed. This is a multi-resolution denoising app-

roach, based on a Stationary Wavelet Transform with Haar mother wavelet, seven levels of decomposition and Universal Threshold.
- **Envelope calculation.** To preserve only the main structure of the signal, root-mean-square upper envelope has been calculated. For that purpose windows of 200 samples have been used.
- **Mean value removal.** The signal modified so far had only positive values. In order to make its mean equal to zero, a mean value removal has been applied.
- **Extract frequency sub-band.** Based on a priori knowledge [7,9], only envelope signal frequencies in the band [0.2, 1.4] Hz have been considered. It was observed that this range is the feasible interval for all possible stride frequencies while walking. To evaluate the envelope frequencies, a filter bank analysis using symlet wavelet with 13 levels of decomposition has been applied.
- **Periodogram computation and max peak evaluation.** The Periodogram of the envelope so filtered has been calculated and the three max peaks have been extracted.

The entire procedure is depicted in Fig. 4.

The second feature has been used to identify when subject slows down or stops. During these events the EMG signal power decreases and becomes near to zero when subject stops walking. The *Root Mean Square* of the signal has been used as feature representative of the signal power [15]:

$$RMS = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{1}$$

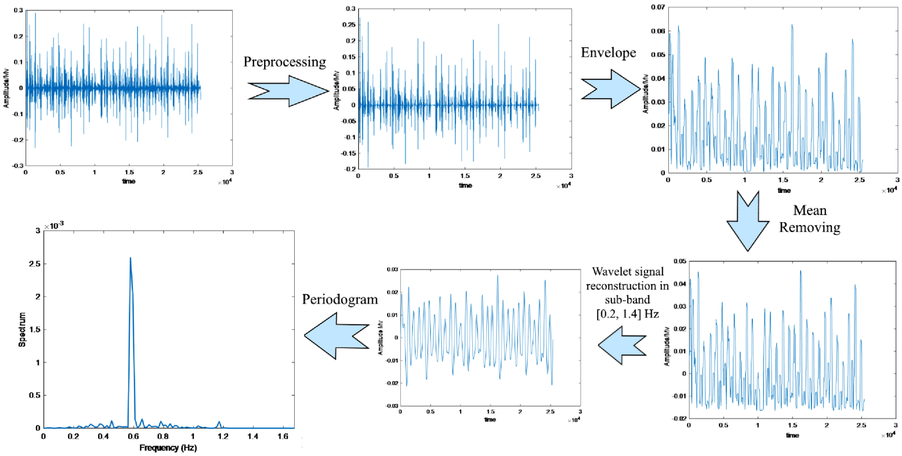


Fig. 4. Procedure applied to extract the Stride Frequency feature

4 Experimental Results

In this section the three different tasks of the experiment are analyzed using the EMG features described and a comparison between young and elderly people behavior is also performed.

Table 1. Accuracy reached by the Frequency Stride feature in evaluating the real pace of the subjects during forced speed walk tasks. The columns refer to the two EMG channels, while the two rows regard the two population groups analyzed.

	Gastrocnemius muscle	Tibial muscle
Elderly	98%	95%
Young adult	98%	98%

Table 2. Accordance in percentage between the computed Stride Frequencies and the metronome frequencies, evaluated with respect to the two muscle activities (columns) and the two considered populations (rows).

	Gastrocnemius muscle				Tibial muscle			
	F1	F2	F3	Total	F1	F2	F3	Total
Young adult	95%	90%	90%	**92%**	95%	90%	85%	**90%**
Elderly	57%	52%	89%	**66%**	68%	58%	92%	**72%**

4.1 Forced Speed Walk

The novel feature here proposed to estimate the Frequency Stride has been initially validated on EMG signals acquired during the forced speed task. During this task, participants were forced to walk at three specific speeds, dictated by a metronome. The subjects repeated these forced speed walks three times. Among all the processed signals, four of them related to the first channel and two related to the second channel have been removed due to low quality and absence of valuable information.

The three metronome speeds were $F1 = 70$, $F2 = 85$, and $F3 = 100$ bpm (beats/minute), and correspond to 1.167, 1.417 and 1.667 steps/second respectively, obtained dividing the metronome speed values by 60. Since the EMG sensor measures the muscle activity of one leg, these frequency values need to be halved to be compared with the values extracted by the proposed feature. The new frequencies used as ground truth become 0.583 steps/second for 70 bpm, 0.708 steps/second for 85 bpm and 0.833 steps/second for 100 bpm.

Firstly the accuracy of the proposed feature in evaluating the real pace of the subjects was assessed. It has been observed that hardly the subjects walked exactly at the speed dictated by the metronome. For this reason, in the evaluation of the performance of the proposed feature, we define the ground-truth following two steps: 1) the coherence between the activities of the two muscles; and 2) visual inspection. The overall accuracy of the measure is 98% considering both the experimental groups. In Table 1, the accuracy of the two population groups obtained analyzing the activity of the two muscles are reported.

As a second analysis, the computed Stride Frequencies were compared with the frequencies of the metronome, in order to compare the capability the two subject groups of following forced paces. In Table 2 the accordance between the subject paces and the three metronome frequencies has been reported, considering the two muscles, and comparing the two experimental groups of young adults and elderly people.

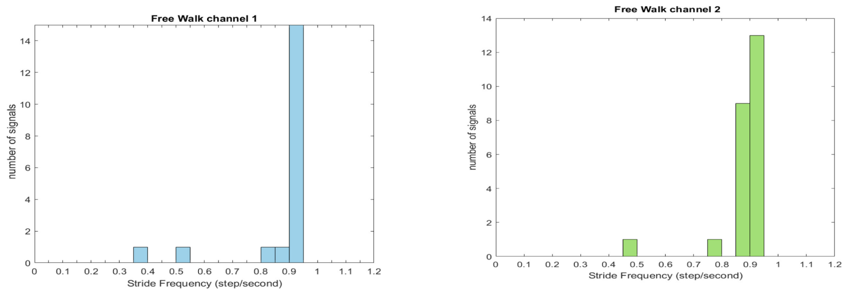
In the case of **young adults**, the percentage of accordance appears high. In details, considering all the metronome frequencies, 92% of accordance has been obtained from the medial gastrocnemius muscle activity, while 90% from the analysis of the tibial muscle one. In general, the forced frequency with the highest accordance was F1 (95% in both the channels) while the worst one was F3 (90% considering gastrocnemius muscle and 85% considering the tibial one).

Table 3. In this Table the mean and the standard deviation of the computed Frequency Stride for both subject groups are reported and compared with the metronome frequencies (F1, F2 and F3), considering both the EMG channels (gastrocnemius muscle and tibial muscle).

	Metronome frequency		Young adults		Elderly	
			Gastrocn.	Tibial	Gastrocn.	Tibial
F1	0.583	Mean	0.59	0.59	0.66	0.64
		Sd	0.02	0.02	0.10	0.09
F2	0.708	Mean	0.72	0.72	0.76	0.74
		Sd	0.02	0.01	0.06	0.10
F3	0.833	Mean	0.85	0.85	0.85	0.85
		Sd	0.02	0.02	0.03	0.02

A significantly lower accordance has been noticed in case of **elderly people**. The overall frequency accordance, evaluated on the first channel was 66%, while on the second one was 72%. The frequency more reproducible was F3, while the worst one was F2. Moreover, as reported in Table 3, the mean and the standard deviation of the Frequency Stride evaluated in case of elderly people appear higher than the ones observed in case of young adults and, in general, the ones dictated by metronome ticking. This may prove how the elderly struggle more than young adults to respect the metronome forced speeds, especially the two lower speeds F1 and F2, tending instead to walk at a faster cadence.

Finally a comparison between the values produced by the feature on the two channels has been performed. In many cases the values produced on the



(a) *Medial gastrocnemius muscle* (b) *Tibial muscle*

Fig. 5. Histograms of the Stride Frequencies computed for the free walk task, on the two muscles.

two signals appeared very similar even if, sometimes, not the same. A distance analysis, performed to compare the results quantitatively, showed that there is not a significant difference between them (root mean square distance = 0.002).

4.2 Free Walk

The same feature was applied to study the free walk task. For the sake of clarity, it is recalled that this task was performed only in the experiment with elderly. For young adults, further experiments will be performed in the future.

In Fig. 5 the histograms of the walking frequencies computed on the two channel signals in the free walk task are reported. Both the histograms highlight that in most of the cases the detected walking frequency is around 0.90 steps/second. This value agrees with the metronome frequency indicated by the participants as the most preferred one (F3) and with the normal pace speed reported in the literature (between 0.90 and 1 steps/second [9]). The lower frequencies in the histograms (0.35 and 0.54 steps/second) correspond to signals where noise and artifacts made difficult to identify the correct one. Usually in these cases a feasible value of human pace could be evaluated from the second or third peak extracted by the proposed feature. Moreover, it has been noted that the presence of other high peaks could be associated to changes in walking pace during the task. An example of a speed change during the free walk task is shown in Fig. 6, where the two different speeds are visible in both the EMG signal and in its Periodogram.

4.3 Collision Avoidance

To analyse changes in EMG signals during the walking task related to collision avoidance, the signal has been initially divided into five segments, using non-overlapping windows. Segments 1, 3, and 5 refer to the free walking phases that precede or follow the collision zone, while segments 2 and 4 refer to the effective pendulum avoidance zone (see Fig. 2). The procedure has been applied to signals

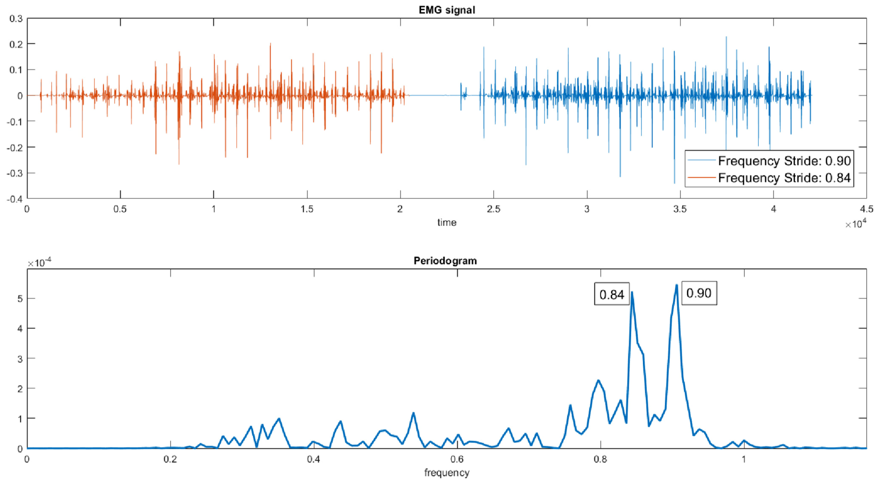


Fig. 6. Example of speed change of one subject during the free walk task. The two different speeds, as well as the two corresponding Frequency Strides, are visible in the EMG signal, (top row) where the two speeds are highlighted with two colors, and in the Periodogram (bottom row), where the two paces are visible as two distinct peaks with similar height. (Color figure online)

Table 4. Stride Frequencies in the five segments of the collision avoidance task, reported in steps/second, evaluated for one subject of the elderly group.

Free Walk	Obstacle	Free Walk	Obstacle	Free Walk
0.94	0.37	0.94	0.5	0.94

from both experimental groups and the Stride Frequency of every segments has been calculated. As an example, in Table 4 the Stride Frequencies (steps/second) calculated for one subject of the elderly group, for the five segments, are reported. The results of this analysis can be summarized as follow:

– For both experimental groups, during the free walking phases of the collision avoidance task (segments 1, 3 and 5), Stride Frequency values similar to those reported by the literature and, in case of elderly, also detected during the free walk task, have been observed. The values related to these segments were usually within the range [0.80–1] steps/second. To quantitatively evaluate the similarity of the walking speeds between: i) the task of pure free walk and ii) the segments of free walk in the collision avoidance task, a statistical similarity analysis using Kruskal Wallis test has been performed. It is important to recall that this analysis can be done only for the elderly, because the young adults did not performed the free walk task. The Kruskal Wallis test on the two distributions produces p-values greater than the significance level of 5% (p-value: 0.263 for Gastrocnemius Muscle and 0.349 for Tibial muscle), indicating that the two distributions can not be distinguished. These results seem to confirm that the pace of walking is not significantly influenced by the presence of an obstacle within the whole path.

– Analysing the values of the Stride Frequency during the free walk phases, before and after the collision avoidance one, it has also been noticed that subjects tend to change frequently their pace during the walking. Even if, in general, they appeared similar in values, the Frequency Strides computed during the walking, before and after passing the obstacle, present a greater variance compared to the one detected during the pure Free Walk task (Sd: 0.22 for Walking with obstacle vs 0.15 for pure Free Walk).

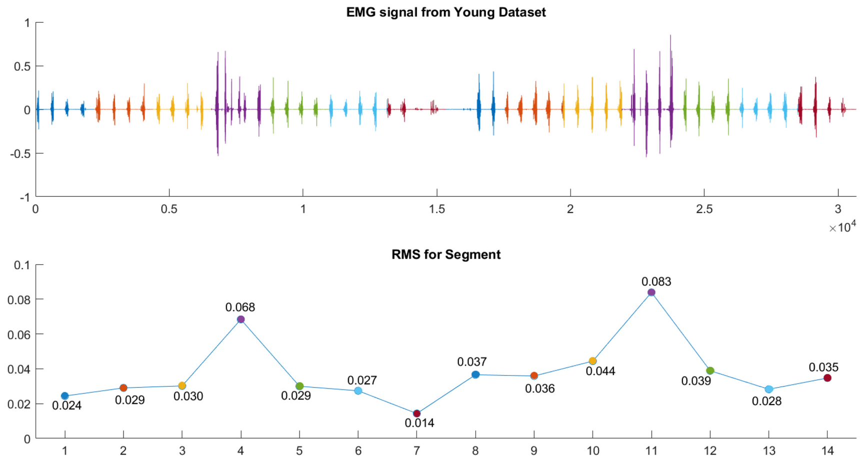


Fig. 7. Analysis on a trial of the collision avoidance task for one young subject. The signal has been divided into fourteen uniform windows (top row). Purple windows correspond to the collision avoidance events. Bottom row reports the trend of the energy values in different segments.

To better understand how does the walking pace change within the collision avoidance zone, an analysis based on signal energy has been performed. This study has been carried out with the idea of detecting stop points or deceleration patterns during this task. The feature chosen for this purpose is the Root Mean Square (RMS), described in Sect. 3.2. For this analysis, the EMG signal of each trial of the collision avoidance task has been now further segmented obtaining fourteen uniform windows.

The energy of the EMG signal has been evaluated for each window using the RMS feature. From the analysis of these RMS values, the following observations can be drawn:

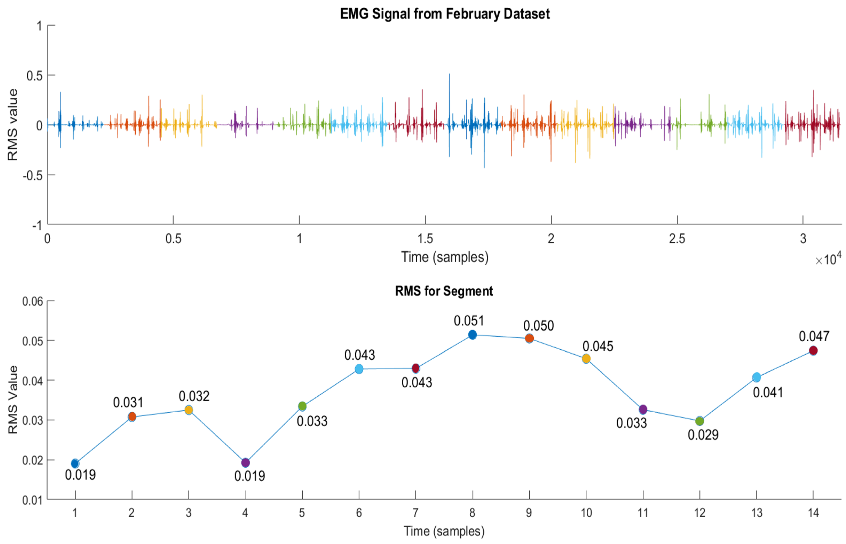


Fig. 8. Analysis on a trial of the collision avoidance task of one elderly subject. The signal has been divided into fourteen uniform windows (Top row). Purple windows correspond to the collision avoidance events. Bottom row reports the trend of the energy values in the different segments. (Color figure online)

– When **young adults** were involved, it has been noticed in general an increase of the signal power in correspondence to the collision avoiding events. Most of the time this growth seems due to a strong muscle activation, probably caused by the effort of the subject to accelerate and safely passing the obstacle, as can be seen in Fig. 7, where one trial of a young subject has been reported. Only in few cases **(5 out of 42)**, participants decided to stop in front of the obstacle. Finally in only one case the subject seemed to be able to pass the obstacle without changing its speed. These results are coherent with what visually observed during the experiment, in which the young adults seemed less inclined to stop than the elderly.
– Analyzing the power of the EMG signals for the **elderly**, in many cases **(29 out of 37)**, it has been observed a decreasing in signal power during collision avoiding events, (see Fig. 8 as an example for one elderly subject). These decreases are related to the observed evidence that, as already mentioned above, the participants decelerated or even stopped, waiting for the pendulum to pass, thus leading to a reduction in the electrical discharge produced by the muscle.

This analysis proves that elderly people are used to keep a more careful behavior than the young ones.

The different behaviour of young adults and elderly in facing up the obstacle has been also investigated using a statistical similarity analysis based on the Kruskal Wallis test, which has been already described in the previous chapter.

This test has been used to compare the two populations (young and elderly) evaluating the energy changes (increase or decrease in percentage) before and after crossing the collision avoidance zone. Two main analyses have been considered:

1. The analysis of the energy variation while crossing, which describes the change in the muscle energy between the free walk phase before the crossing and the crossing itself. The percentage of this variation has been calculated by the formula:
$$\frac{RMS_{crossing} - RMS_{beforeCrossing}}{RMS_{beforeCrossing}} \tag{2}$$
The segment corresponding to the crossing ($RMS_{crossing}$) and the segment before it ($RMS_{beforeCrossing}$) are considered in this calculation.
2. The analysis of the energy variation after the crossing, which instead represents the change of muscle energy between the crossing and the free walk phase which follows it. The percentage of this variation has been calculated by the formula:
$$\frac{RMS_{afterCrossing} - RMS_{crossing}}{RMS_{crossing}} \tag{3}$$
In this case, the two segments involved were the segment after the crossing ($RMS_{crossing}$) and the one relating to the crossing itself ($RMS_{beforeCrossing}$).

For both the two formulas, a positive percentage corresponds to an energy increment. On the other hand, a negative percentage refers to a decrease in energy. From these data the following analyses have been performed:

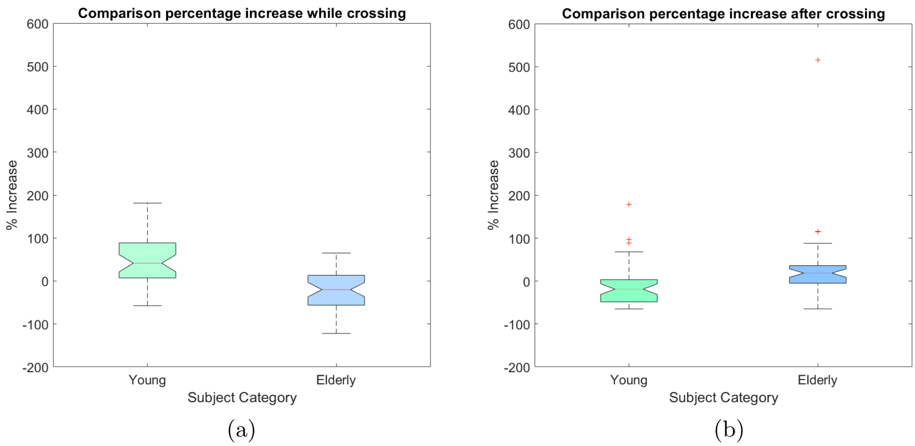


Fig. 9. Boxplots concerning the percentage increase of muscle energy detected in the two population analyzed (young adults and elderly) due to the crossing (Fig. 9a) and after that (Fig. 9b). A positive value corresponds to an increase in muscular energy, while a negative percentage represents a decrease in the energy value.

- **Energy variation while crossing**: the Kruskal Wallis test has been used to compare the two populations (young adults and elderly). A p-value lower than 0.001 has been obtained, thus the two distributions of energy variations are different. Moreover, as reported in the boxplot of Fig. 9a, in case of the elderly, the energy in general decreases, while in the case of young adults it increases, in agreement with what already described above, regarding the different behaviour between young adults and elderly.
- **Energy variation after crossing**: In this case, the elderly tend to increase their speed once passed the obstacle, unlike the young adults that tend to decelerate to come back to their previous speed. This different behaviour is once more visible from the comparison of the two populations applying the Kruskal Wallis test. Even in this case, in fact, the test generates a p-value very low (p-value < 0.001). The different values detected for the two populations are visible in Fig. 9b.

A final observation regards the differences between the signals of the two channels. The EMG signals acquired from the tibial muscle appeared in general more affected by noise that the ones recorded from the medial gastrocnemius muscle. Sometimes these artifacts negatively affected the power detected on the signals considered. For this reason the analysis presented in this section has been carried out considering only data collected from the first channel.

5 Conclusions

The analysis reported in this paper is part of an extensive study where physiological signals are adopted to assess walkability, especially in case of elderly. These studies are based on both *in-vitro* (i.e. in a controlled laboratory environment) and *in-vivo* (i.e. in a real uncontrolled scenario) experiments. In particular, the results obtained with the analysis of the EMG during different walking conditions confirm that physiological responses can give significant hints in studying pedestrian behaviour and their reactions and confidence within different environments. Moreover, this analysis permits to underline the different behaviour of the elderly with respect to young adults. In particular, the two population groups would need a more specific and in-depth analysis to create ad-hoc environments able to meet their needs. The results here reached, can be useful in different analysis, for instance, they may be used to better understand the age-related behaviour of subjects in real-world stressful urban environments like, for example, busy street or uncomfortable and crowded sidewalks. Besides, the novel methods of signal processing introduced in this paper (like, for example, the use of the periodogram to identify the walking speed) may be used in future works to analyse people gait in different situations or to predict the behaviour or subjects' status on the basis of their physiological responses. In future work the analysis on GSR and PPG as well as on inertial data will be performed and merged with the analysis on EMG data. There are, indeed, different works, in the state of art, that proves the goodness of these others signals in the research area of gait analysis. In particular, promising results have been reached using Inertial Motion Units (IMUs) [8,14] and the combination of them and the EMG signals [19]. In addiction, further experiments will be performed to collect more data that will permit classification of the tasks, based both on traditional machine learning techniques as well as deep learning approaches. In particular, the use of Neural Networks like the Long Short Term Memory LSTM, looks very promising [14] especially in distinguishing age-related differences in walking [8]. With respect to this topic, our near-future work will be mainly related to adopt pre-trained networks, fed with properly adapted data. For instance, converting monodimensional physiological signals into 2-D time-frequency data will permit to consider well-known CNNs.

Acknowledgment. This research is partially supported by Fondazione Cariplo, for the project LONGEVICITY - Social Inclusion for the Elderly through Walkability (Ref. 2017-0938) and by the Japan Society for the Promotion of Science (Ref. L19513). We want to give our thanks to Kenichiro Shimura and Daichi Yanagisawa, for their supporting work during the experimentation.

References

1. Bandini, S., Gasparini, F.: Towards affective walkability for healthy ageing in the future of the cities. In: Proceedings of the 5th Workshop on Artificial Intelligence for Ambient Assisted Living, AIxIA 2019, vol. 2559. CEUR-WS (2020)
2. U.S. Census Bureau: 2017 National Population Projections Datasets (2017)
3. Can, Y.S., Arnrich, B., Ersoy, C.: Stress detection in daily life scenarios using smart phones and wearable sensors: a survey. J. Biomed. Inform. **92**, 103139 (2019)
4. Donoho, D.L., Johnstone, J.M.: Ideal spatial adaptation by wavelet shrinkage. Biometrika **81**(3), 425–455 (1994)
5. Gaglione, F., Cottrill, C., Gargiulo, C.: Urban services, pedestrian networks and behaviors to measure elderly accessibility. Transp. Res. Part D: Transp. Environ. **90**, 102687 (2021)
6. Halaki, M., Ginn, K.: Normalization of EMG signals: to normalize or not to normalize and what to normalize to. In: Computational Intelligence in Electromyography Analysis-A Perspective on Current Applications and Future Challenges, pp. 175–194 (2012)
7. Hoeger, W.W., Bond, L., Ransdell, L., Shimon, J.M., Merugu, S.: One-mile step count at walking and running speeds. ACSM's Health Fitness J. **12**(1), 14–19 (2008)
8. Hu, B., Dixon, P., Jacobs, J., Dennerlein, J., Schiffman, J.: Machine learning algorithms based on signals from a single wearable inertial sensor can detect surface-and age-related differences in walking. J. Biomech. **71**, 37–42 (2018)
9. Ji, T., Pachi, A.: Frequency and velocity of people walking. Struct. Eng. **84**(3), 36–40 (2005)
10. Kim, H.: Wearable sensor data-driven walkability assessment for elderly people. Sustainability **12**(10), 4041 (2020)
11. King, A.C., et al.: Employing participatory citizen science methods to promote age-friendly environments worldwide. Int. J. Environ. Res. Public Health **17**(5), 1541 (2020)

12. Le, T.P.L., Leung, A., Kavalchuk, I., Nguyen, H.N.: Age-proofing a traffic saturated metropolis-evaluating the influences on walking behaviour in older adults in Ho Chi Minh City. Travel Behav. Soc. **23**, 1–12 (2021)
13. Lee, G., Choi, B., Jebelli, H., Ahn, C.R., Lee, S.: Wearable biosensor and collective sensing-based approach for detecting older adults' environmental barriers. J. Comput. Civ. Eng. **34**(2), 04020002 (2020)
14. Moon, S., et al.: Classification of Parkinson's disease and essential tremor based on balance and gait characteristics from wearable motion sensors via machine learning techniques: a data-driven approach. J. NeuroEng. Rehabil. **17**(1), 1–8 (2020)
15. Phinyomark, A., Limsakul, C., Phukpattaranont, P.: A novel feature extraction for robust EMG pattern recognition. arXiv preprint arXiv:0912.3973 (2009)
16. Wei, G., Tian, F., Tang, G., Wang, C.: A wavelet-based method to predict muscle forces from surface electromyography signals in weightlifting. J. Bionic Eng. **9**(1), 48–58 (2012)
17. Wren, M.A., et al.: Projections of demand for healthcare in Ireland, 2015–2030: first report from the Hippocrates model. ESRI Research Series Number 67 October 2017 (2017)
18. Yetisen, A.K., Martinez-Hurtado, J.L., Ünal, B., Khademhosseini, A., Butt, H.: Wearables in medicine. Adv. Mater. **30**(33), 1706910 (2018)
19. Zhang, X., Tang, X., Zhu, X., Gao, X., Chen, X., Chen, X.: A regression-based framework for quantitative assessment of muscle spasticity using combined EMG and inertial data from wearable sensors. Front. Neurosci. **13**, 398 (2019)