EMG for walkability assessment: a comparison between elderly and young adults

Francesca Gasparini[a], Alessandra Grossi[a], Katsuhiro Nishinari[b] and Stefania Bandini[a,b]

[a]Department of Computer Science, Systems and Communications, University of Milano - Bicocca, Italy

[b]RCAST - Research Center for Advanced Science & Technology, The University of Tokyo

Abstract

Populations around the world are rapidly ageing, and the need to ensure healthy aging is one of the main priorities of modern society. Living and moving in environments that support and maintain intrinsic capacity and functional ability are important aspects related to healthy ageing. 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. This work proposes to assess walkability, evaluating the safety perception of different walking conditions, relying on physiological responses. 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 muscles activity acquired with Electromyography is presented as a preliminary study.

Keywords

physiological signals, active ageing, walkability, affective state, collision avoidance, Elettromiography,

1. Introduction

In recent years, an increase of longevity in developed countries has been observed [1][2][3]. Growth of social welfare, education, medical care are only few of the possible reasons for this increase[4]. 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. 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 activities [3]. Furthermore, some studies underline that physical activity plays an important role in aging people's health

AIXAS2020: Italian Workshop on Artificial Intelligence for an Ageing Society, November 25th-27th, 2020
EMAIL: francesca.gasparini@unimib.it (F. Gasparini); a.grossi6@campus.unimib.it (A. Grossi); tknishi@mail.ecc.u-tokyo.ac.jp (K. Nishinari); stefania.bandini@unimib.it (S. Bandini)
ORCID: 0000-0002-6279-6660 (F. Gasparini); 0000-0002-7056-0543 (S. Bandini)

as its practice allows to avoid physical or mental illnesses[5]. 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. Measuring if and to which extent an environment is comfortable and walkable for ageing people is the first step towards this direction. 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 [6].

Physiological responses, which are uncontrolled and autonomous reactions of our nervous system, can be considered honest indicators of our emotions and mood, and are nowadays widely adopted to recognize affective states [7]. Thanks to the development of the technology, several sensors can be easily integrated into smartphones or wearable devices [8], 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 as we are dealing with a dynamic interaction we add motion data both physiological, measuring the muscle activity with Electromyogram (EMG), and inertial (accelerometer and gyroscope data).

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 Section 2, the *in-vitro* experiment performed to assess walkability is introduced. EMG signal processing is described in Section 3, while the results of the analysis of different walking conditions and the comparison of the behaviour of the two populations are detailed in Section 4. Finally conclusions and future works are reported.

2. Affective walkability assessment

The affective walkability assessment has been performed with a controlled laboratory experiment at the University of Tokyo, composed of three within subject conditions (collision

Figure 1: Wearable devices adopted.

avoidance, forced speed walk and free walk) administered in one experimental session, performed by two experimental groups: a population of young adults, composed of 14 Japanese master and PhD students, with an average age of 24.7 years (22 - 34 years old, standard deviation = 3.3, 4 women), and Japanese elderly people (retired), 20 subjects, with an average age of 65.15 years (60-70 years old, 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:

- **Galvanic Skin Response (GSR)**: also known as Skin Conductance (SC), which is connected to sweating and perspiration on the skin
- **Photoplethysmography (PPG)**: that measures the blood volume registered just under the skin, which can be used to obtain the heart rate of the subject
- **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.
- **Accelerometer** and **Gyroscope** data

The adopted sensors are shown in Figure 1.

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

- **Collision avoidance**. In the first task, two subjects at the same time walk with their own pace along the path depicted in Figure 2, top left, clockwise and counterclockwise respectively. At about half of the path, they reach the collision avoidance zone where

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

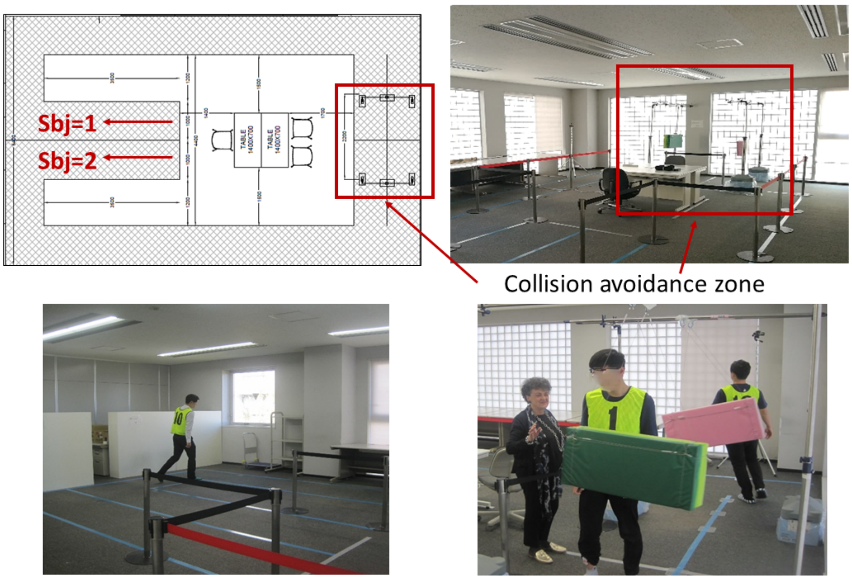


Figure 2: Setting of the *in-vitro* experiment. Top left: the plant of the indoor controlled environment, where a *U* path has been defined. The collision avoidance zone is identified by a red rectangle and depicted also in the image at the top right. The two obstacles are controlled by one of the experimenter 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.

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.

- **Forced speed walk**. The second task is about stressful walking. In this part of the experiment participants have to walk to 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 last about 2 minutes. At the end, a questionnaire is provided to the participants to obtained information about the preferred walking frequency among those constrained by the metronome.
- **Free walk**. A normal walking phase is performed along the *U* path, back and forth, for about 40 seconds. In this task participants can walk freely without obstacles or speed constraints.

The tasks are separated by a period of resting time (**Baseline acquisition**) of about 1 minute. 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.

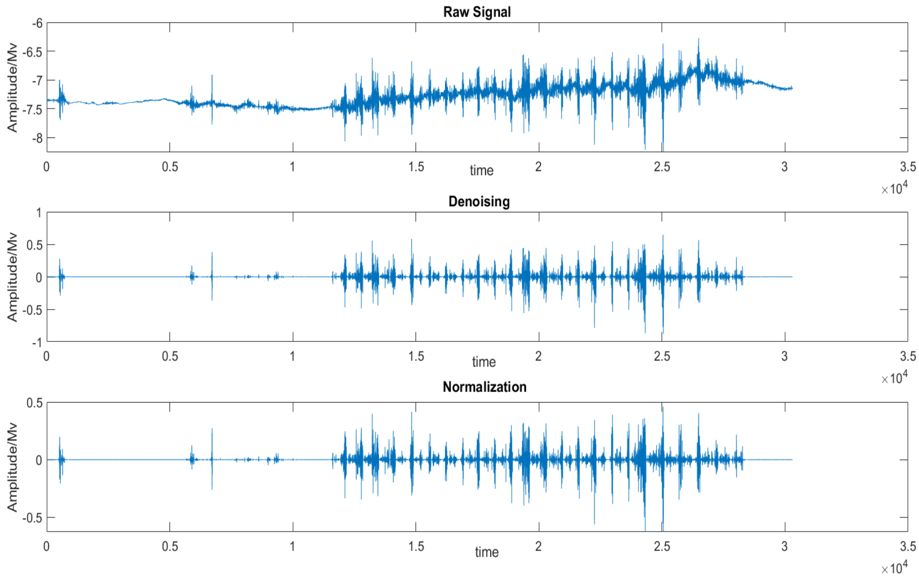


Figure 3: Example of the applied preprocessing procedure on the EMG signal of a subject. Top image: the raw signal. Middle image: the results of the denoising procedure on the signal. Last image: Result of the normalization.

3. EMG data analysis

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

3.1. Subject based preprocessing

For each subject, the entire EMG raw signal for each channel have been preprocessed by applying a denoising strategy based on the wavelet multi-resolution analysis described in [9]. After that, 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, [10]. 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 figure 3.

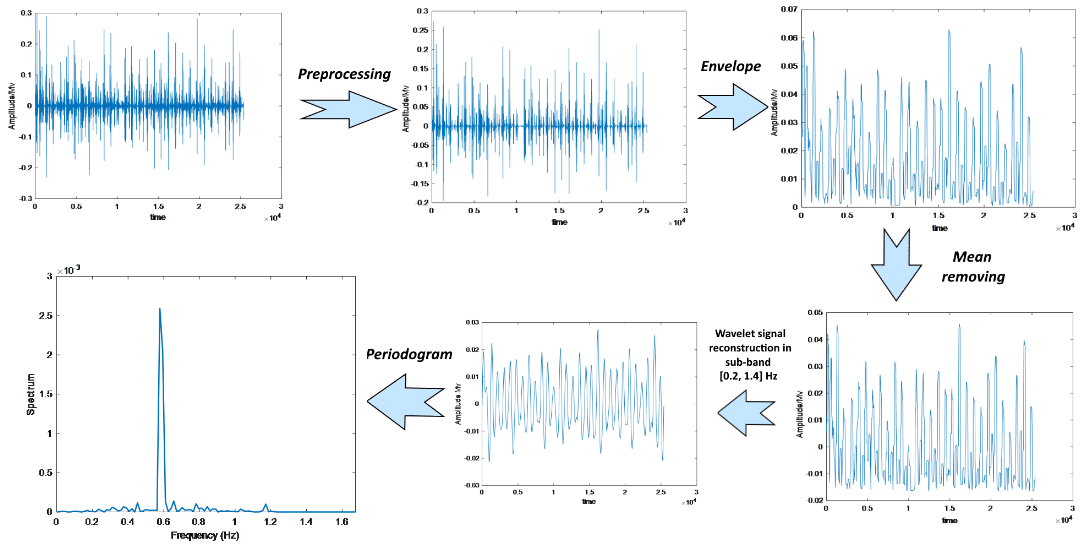


Figure 4: Procedure applied to extract the stride frequency feature

3.2. EMG features extraction

To compare different walking conditions and different behaviours in the two considered populations, two features have been extracted from the denoised and normalized EMG signals described in Section 3.1: walking frequency (known as Stride Frequency) and mean power of the signal. The first feature describes the number of steps performed by a subject per second. It was extracted from the EMG signal using a novel procedure described in this paper:

- **Task based preprocessing**. To further remove artifacts and noise, a task based denoising has been performed. Once again it has been used a multi-resolution wavelet denoising approach.
- **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 [11], [12], only envelope signal frequencies in the band [0.2, 1.4] Hz have been considered. It was observed, in fact, 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**. At the end the Periodogram of the envelope so filtered has been calculated and the three max peaks have been extracted.

The entire procedure is depicted in figure 4.

The second feature has been used to identify when subject slows down or stops. During these events, in fact, signal decreases its power that becomes near to zero when subject stops walking. For this reason it has been decided to use the *Root Mean Square* of the signal as signal power representative feature [13]. It has been calculated using the formula:

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

4. Analysis of the 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. The three tasks are listed below for the sake of clarity, recalling that each of them were repeated three times:

1. Forced speed walk;
2. Free walk;
3. Collision Avoidance.

4.1. Forced speed walk

The novel feature here proposed to estimate the walking frequency 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 (beat/minute), and correspond to 1.167, 1.417 and 1.667 step/second respectively, obtained dividing the metronome speed values by 60.
These values refer to the stride frequency made moving both the legs. 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 step/second for 70 bpm, 0.708 step/second for 85 bpm and 0.833 step/second for 100 bpm.

Firstly the accuracy of the proposed feature in evaluating the real pace of the subjects was evaluated. Due to the human nature of the participants, it has been observed that hardly they 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 groundtruth following three steps: 1) the frequency values of the metronome, admitting a deviation of +/- 0.04; 2) the coherence between the activity of the two muscles; and 3) 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.

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

Table 1

Accuracy reached by the feature Frequency Stride in evaluating the real pace of the subjects during forced speed walk tasks. The two columns refers to the EMG channels on which the features have been extracted, while the two rows regard the two population groups analyzed.

	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%**

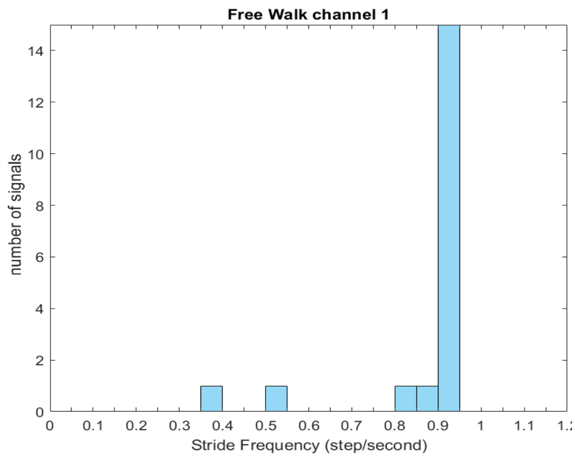
Table 2

Percentage of times in which the category of subjects indicated on the row respected the metronome frequency imposed by the task indicated in the column. The first four columns are about signals acquired on the first EMG channel while the last four columns regard the signals acquired on the second channel.

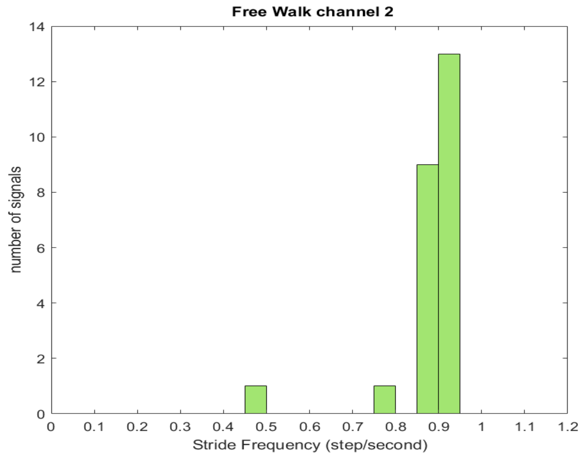
As a second analysis, the stride frequencies of the subjects were compared with the frequencies of the metronome, in order to quantify with respect to the two different populations, their ability in following a forced pace. In the dataset collected involving young adults, the percentage of accordance between the stride frequencies and the metronome frequency is high. In details, taking into account all the three tasks, corresponding to the three frequencies of the metronome, 92% of accordance has been obtained in the signal acquired from medial gastrocnemius muscle, while 90% has been obtained from the analysis of the tibial muscle activity. In general, the frequency with the highest accordance was F1 (95% in both the channels) while the worst one was F3 (90% with signals acquired on the Gastrocnemius Muscle while 85% with signals acquired on the Tibial Muscle).

Lower accordance has been noticed in the dataset concerning elderly people. In fact 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. These results differ from what emerged in the analysis of the young adults. Actually, from a deeper study of the values produced, it has been observed that the elderly struggle to respect the metronome forced speeds (especially the half speed F2) tending instead to walk at a faster cadence, more similar to their usual pace. Table 2 reports the accordance between the subject paces and the metronome frequencies evaluated from the two muscles, in the three different tasks and comparing the two experimental groups of young adults and elderly people.

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 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).



(a) *Channel 1 (medial gastrocnemius muscle)*



(b) *Channel 2 (tibial muscle)*

Figure 5: *Histograms of the stride frequencies calculated on the free walk task, on the two channel EMG signal.*

4.2. Free walk

The same feature was applied to study the free walk task. In figure 5 the histograms of the walking frequencies evaluated on the two channel signals of the free walk task are reported. Both the histograms highlight how in most of the cases the detected walking frequency is around 0.90 step/second. This value agrees with the metronome frequency indicated by the participants as the most preferred (F3) and with the normal pace speed reported in the literature (between 0.90 and 1 step/second [12]). The lower frequencies in the histograms (0.35 and 0.54 step/second) regard signals where the noise and artifacts made difficult to identify the correct stride frequency. 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.

4.3. Collision avoidance

To analyse changes in EMG signals during the stressful walking task related to collision avoidance, the signal has been initially divided into five segments using non overlapped windows. Segments 1, 3 and 5 refer to the free walking phases that preceded or followed the obstacle zone crossing, while segments 2 and 4 refer to the effective pendulum avoidance zone.
The procedure has been applied to signals from both experimental groups and the stride frequency of every segments has been calculated. In Table 3 the stride frequencies (step/second) calculated for one subjects within the five segments are reported. The results of the analysis of this task can be summarized as follow:

- For both experimental groups, during the free walking phases of the collision avoidance

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

Table 3
Stride frequencies in the five segments of the collision avoidance task, reported in step/second, evaluated for one subject.

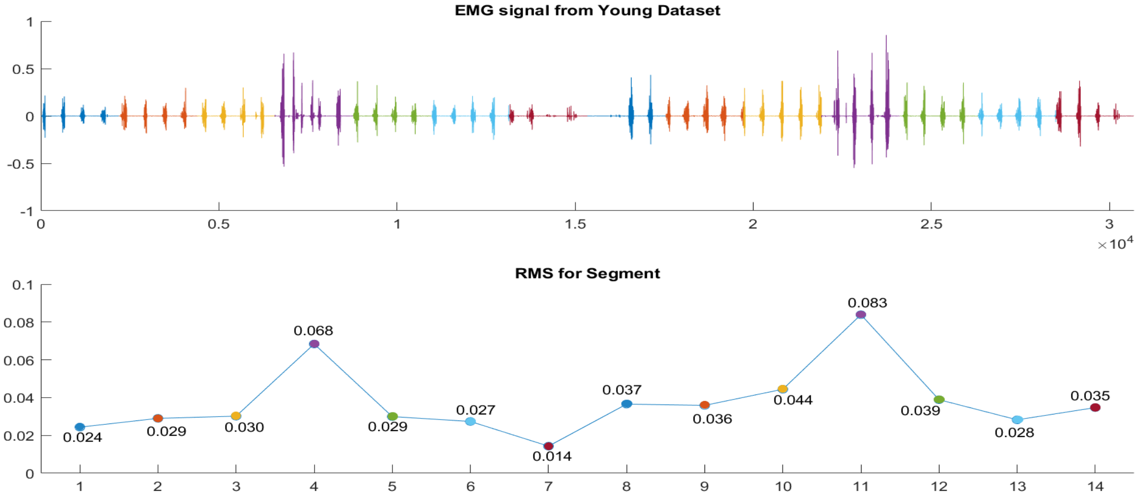


Figure 6: *Analysis on a trial of collision avoidance task for one young subject. The signal has been divided into fourteen uniform windows (top row). Purple windows correspond to the collision avoidance events. Bottom row reports the trend of the energy values in different segments.*

task (segments 1, 3 and 5), values of stride frequency similar to those detected during the free walk task have been observed. The values related to these segments were usually within the range [0.80 - 1] step/second. Therefore, from these results, it seems 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 walking phases before and after the obstacle, it has been also noticed how subjects tend to change their pace.
- Interesting information has been extracted from the analysis of the segments concerning obstacle crossing (segments 2 and 4). In this cases, the stride frequency identified by the algorithm is low with values near to 0.37 step/second, mainly related to real deceleration or stop in subject's walking. However, these signals are also often affected by noise and artifacts.

To better understand how the walking pace changes within the collision avoidance zone crossing, 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 stressful task. The feature chosen for this purpose is the Root Mean Square (RMS), described in Section 3.2. For this analysis,

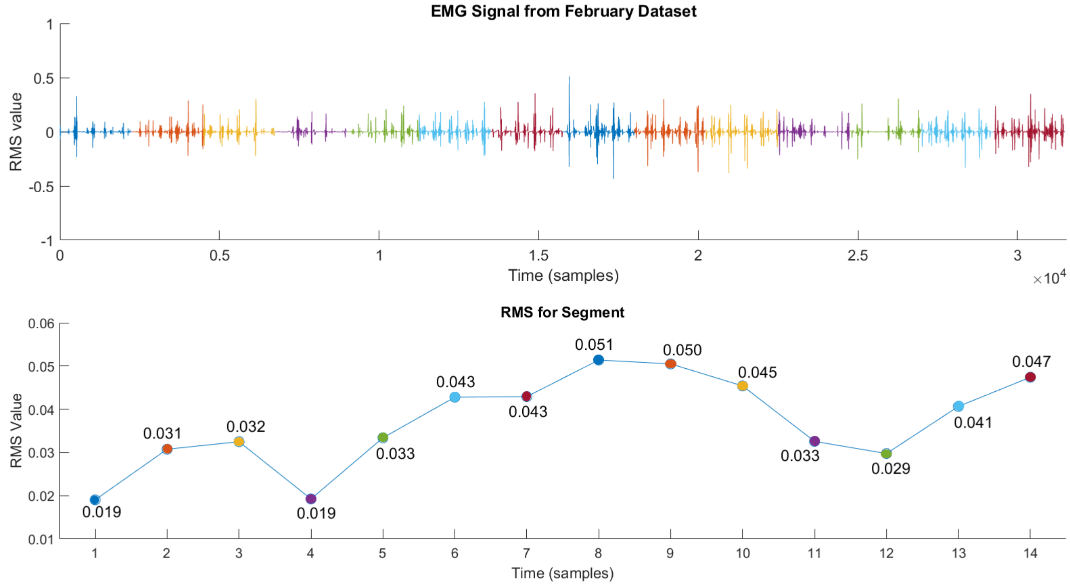


Figure 7: *Analysis on a trial of collision avoidance task for one elderly subject. The signal has been divided into fourteen uniform windows (Top row). Purple windows correspond to the collision avoidance events. Bottom row reports the trend of the energy values in the different segments.*

the EMG signal of each trial of the collision avoidance task has been manually segmented obtaining fourteen uniform windows.

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

- When **young adults** were involved, it has been usually noticed 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, see Figure 6. 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 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 Figure 7. These decrease is 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.

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

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 urban environments. Moreover this analysis permits to underline the different behaviour of the elderly with respect to young adults. 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. 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. These latter approaches will be mainly related to adopt pre-trained networks, fed with properly adapted data, for instance converting modimensional physiological signals into 2-D time frequency data, that will permit to consider CNNs.

Acknowledgments

This research is partially supported by the FONDAZIONE CARIPLO “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] M.-A. Wren, C. Keegan, B. Walsh, A. Bergin, J. Eighan, A. Brick, S. Connolly, W. Dorothy, J. Banks, Projections of demand for healthcare in Ireland, 2015-2030: first report from the Hippocrates model. Esri research series number 67 October 2017, 2017.

[2] U. C. Bureau, 2017 national population projections datasets, 2017.

[3] H. Kim, Wearable sensor data-driven walkability assessment for elderly people, Sustainability 12 (2020) 4041.

[4] A. C. King, D. K. King, A. Banchoff, S. Solomonov, O. Ben Natan, J. Hua, P. Gardiner, L. G. Rosas, P. R. Espinosa, S. J. Winter, et al., Employing participatory citizen science methods to promote age-friendly environments worldwide, International Journal of Environmental Research and Public Health 17 (2020) 1541.

[5] G. Lee, B. Choi, H. Jebelli, C. R. Ahn, S. Lee, Wearable biosensor and collective sensing–based approach for detecting older adults' environmental barriers, Journal of Computing in Civil Engineering 34 (2020) 04020002.

[6] S. Bandini, F. Gasparini, Towards affective walkability for healthy ageing in the future of the cities, in: Proc. 5th Workshop on Artificial Intelligence for Ambient Assisted Living (AIxIA 2019), volume 2559, CEUR-WS, 2020.

[7] Y. S. Can, B. Arnrich, C. Ersoy, Stress detection in daily life scenarios using smart phones and wearable sensors: A survey, Journal of biomedical informatics (2019) 103139.

[8] A. K. Yetisen, J. L. Martinez-Hurtado, B. Ünal, A. Khademhosseini, H. Butt, Wearables in medicine, Advanced Materials 30 (2018) 1706910.

[9] G. Wei, F. Tian, G. Tang, C. Wang, A wavelet-based method to predict muscle forces from surface electromyography signals in weightlifting, Journal of Bionic Engineering 9 (2012) 48–58.

[10] M. Halaki, K. Ginn, Normalization of emg signals: to normalize or not to normalize and what to normalize to, Computational intelligence in electromyography analysis-a perspective on current applications and future challenges (2012) 175–194.

[11] W. W. Hoeger, L. Bond, L. Ransdell, J. M. Shimon, S. Merugu, One-mile step count at walking and running speeds, ACSM's Health & Fitness Journal 12 (2008) 14–19.

[12] T. Ji, A. Pachi, Frequency and velocity of people walking, Structural Engineer 84 (2005) 36–40.

[13] A. Phinyomark, C. Limsakul, P. Phukpattaranont, A novel feature extraction for robust emg pattern recognition, arXiv preprint arXiv:0912.3973 (2009).