Measurement: Sensors 38 (2025) 101648

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

Evaluation of physical effort by IoT-based wearable sensors

ARTICLE INFO

Keywords:
Biomedical measurement system
Wearable devices
Internet-of-Things (IoT)
Skin conductance
Electromyography
Physical effort

ABSTRACT

Assessment of physical effort commonly addressed in research through acceleration signals can show significant measurement errors. The approach presented in this paper formulates a proper measurement system to evaluate the physical effort by wearable devices. Specifically, the paper proposes the joint use of sensors for skin conductance (SC) and electromyography (EMG). The EMG sensor is introduced uniquely with the aim of properly identifying the effort level. The classification is, instead, entirely entrusted to the SC signal alone. The proposed approach is then tested in the evaluation of muscular fatigue felt by arms. The experimental results show good performance, as the obtained values in terms of classification accuracy and sensitivity are, respectively, 84.68 % and 89.75 %.

1. Introduction

The World Health Organization has developed guidelines regarding physical activity and sedentary behaviur, to promote a healthy lifestyle among citizens and reduce the rate of incidence of chronic illnesses on populations, especially in developed countries [1]. In Ref. [1], the intensity of physical activity is expressed in metabolic equivalent of task (MET), which is defined as the energy expended by a subject while seated at rest, and it is usually related to the oxygen consumed by the subject. For this reason, MET can be quantified by measuring the subject oxygen uptake, through laboratory equipment and individual calibration. Anyway, several research studies have shown that also monitoring of physiological signals can produce suitable results in estimating the intensity of physical activity [1–3].

Nowadays, measurement of physiological signals has been moving in the direction of remote monitoring, through the Internet-of-Things (IoT) paradigm and the use of wireless sensing devices. In fact, wearable devices enable long-term monitoring of performed activities and physiological parameters, potentially anytime and anyplace. This way, smart acquisition of physiological signals can be exploited to monitor people in healthcare centers as well as in everyday life. Moreover, the early detection of anomalies in physiological signals can be considered one of the main advantages in adopting the IoT paradigm to prevent serious pathologies [4].

In literature, evaluation of physical effort is typically addressed through acceleration and heart rate signals [5–7]. Indeed, wearable devices equipped with accelerometers and inertial measurement units can be used to quantify physical activity, because they allow to estimate both its time duration and intensity, by measuring three-dimensional acceleration of body locations [5]. In general, metrics computed from jerk, the time derivative of acceleration, can be considered indicators of physical exertion and fatigue, with better classification performance than features computed from heart rate [6]. Jerk can be employed to evaluate motor control capabilities, discriminating between pathological and non-pathological conditions [6]. Furthermore, accelerometers can be combined with a heart rate sensor, as in Ref. [7], where a measurement system based on such sensors is employed to analyze physical work demands. A similar joint analysis has also the great advantage that, in some cases, accelerometers and heart rate sensors can be simultaneously embedded in wearable devices [8,9]. However, despite improved data processing and proposed calibration techniques, evaluation of physical activity based on accelerometers shows significant measurement errors, hindering their extensive applicability in clinical research and practice [10].

In reality, physical fatigue is the result of several physiological processes, where multiple peripheral systems (such as cardiovascular and thermoregulatory systems) interact with the brain to produce a response [11]. During the development of physical fatigue, these contributing mechanisms reduce the ability of muscle fibers to generate force [12]. Thus, above all, electromyogram (EMG) should be considered, especially when performing remarkable efforts [13]. Integrated EMG and also amplitude and time position of peak computed for the linear envelope are common EMG metrics [14].

In recent years, the signal of skin conductance (SC) - also called electrodermal activity - has been investigated in pathophysiological applications [15,16], since able to detect conditions of psycho-physical stress such as pain or fatigue. Essentially, SC consists of a rapid response (the skin conductance response [17]) plus a slow variation (the skin conductance level [18]) to stimuli of different nature [19]. Just to cite an example, as reported in Ref. [20], SC may be exploited to evaluate nociceptive response during movement activities.

The idea behind this research is to devise a proper measurement

https://doi.org/10.1016/j.measen.2024.101648

Available online 31 December 2024

system to evaluate the physical effort by wearable devices. Contrarily to literature techniques based on only acceleration and, possibly, heart rate, a sensor fusion approach combining manifestations of physical effort in more signals can improve accuracy and reproducibility of outcomes, despite the intrinsic variability of the observed phenomenon. Therefore, this paper proposes the joint use of sensors for SC and EMG. The EMG sensor is introduced with the aim of suitably identifying the effort level. Then, the classification phase is entirely entrusted to a Machine Learning (ML) algorithm, fed with the information content carried out by the SC signal alone. The input of the classification is the normalized amplitude of the SC signal, while the output is a binary value of low effort or high effort.

The rest of the paper is organized as follows. Section 2 presents the proposed approach, describing the measurement system for acquisition of SC and EMG signals and the evaluation of physical effort. Section 3 shows the experimental results of the implemented tests. Finally, Section 4 concludes the paper.

2. Proposed approach

This Section describes the proposed approach, which consists in conceiving a measurement system to evaluate physical effort. Specifically, the approach is proposed for evaluation of muscular fatigue felt by arms. Thus, a set of sensors is located on upper limbs of monitored subjects. Subsequently, the signals acquired by the sensors are properly analyzed.

2.1. Measurement system for SC and EMG signals

The conceived measurement system is based on fusion of SC and EMG sensors, here proposed for evaluation of muscular fatigue felt by arms. In particular, the sensors of SC and surface EMG are jointly placed, as shown in Fig. 1, on the non-dominant upper limb of six subjects. The monitored subjects are chosen on purpose by dividing equally between men and women. The acquisitions of the two sensors occur simultaneously. The SC signals are acquired at a sampling frequency of $f_{SC} = 4$ Hz by an Empatica E4, a multi-sensor device that is worn on the wrist [8]. For SC detection, the Empatica employs the exosomatic methodology, since two dedicated electrodes, in contact with the skin on the ventral wrist, are crossed by an alternating current of 100 μA, generated at a frequency of 8 Hz. Instead, the surface EMG signals are acquired by a BTS Bioengineering Freeemg system at a sampling frequency of $f_{EMG} =$ 1000 Hz. In detail, a single bipolar electrode for surface EMG is located in correspondence of the flexor carpi radialis in order to monitor a motor task for muscular fatigue.

During the data acquisition protocol, the subjects seat on a chair with their non-dominant arm on an adjustable support, without the possibility of moving shoulder and rotating elbow, wrist joint, hand, and fingers (see Fig. 1). Then, they are asked to perform a series of wrist flexions by contracting the forearm muscles of their non-dominant arm, for an overall duration of $\Delta = 4$ min. This specific motor task is intentionally chosen for eliciting fatigue with an isometric muscular configuration, since no actual arm movement takes place. Indeed, the isometric configuration allows a correct detection of muscular fatigue [21].

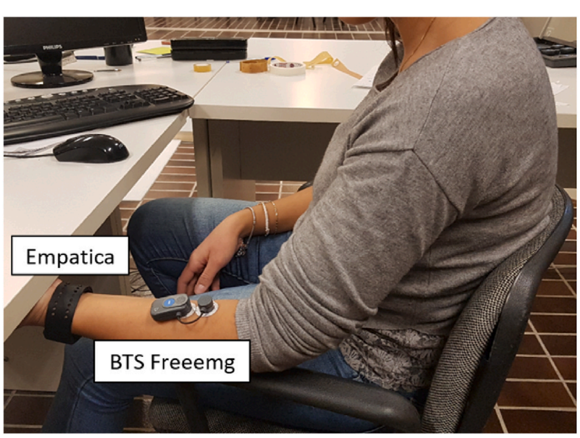

Fig. 1. Sensors adopted for evaluation of physical effort: the Empatica worn on the wrist and the BTS Freeemg located on the flexor carpi radialis.

Once the acquisition session terminates, the signals collected by both the sensors can be downloaded for evaluation of physical effort. In the case of Empatica, the signals are stored in a remote cloud, while, in the case of BTS Freeemg, the signals are recorded in a local platform.

2.2. Evaluation of physical effort

The proposed method is intended to classify the intensity level of physical effort for the six monitored subjects. The physical effort is evaluated from SC and EMG as described below. The feature extraction and the classification of physical effort are carried out by considering the SC signal. The EMG signal is, instead, employed exclusively to label the levels of physical effort on the SC signal. A similar approach can be realized thanks to the simultaneous acquisition of SC and EMG signals. Therefore, the proposed approach can be summarized in three main steps: (i) feature extraction from the SC signal; (ii) identification of effort levels through the EMG signal; (iii) classification of physical effort on the SC signal.

In the first step, the acquired SC samples $x(n)$ are normalized as follows:

$$x_{norm}(n) = \frac{x(n)}{x_{max}} \tag{1}$$

where $n = 1,2,\dots,\Delta f_{SC}$, while x_{max} is the maximum value of the signal x during the entire acquisition of duration Δ. For each subject, the sample of normalized SC amplitude $x_{norm}(n)$ is the only extracted feature to label in the second step, and recognize in the last step of classification.

Subsequently, two levels of physical effort are identified depending on the EMG signal. In other words, the EMG signal is employed as a reference to discriminate between low effort and high effort. The assessment of muscular fatigue from the EMG signal of the flexor carpi radialis is performed by relying on the median frequency (MDF) of the EMG power spectrum. In fact, computing the MDF of the EMG power spectrum represents a well-acknowledged method for fatigue quantification when dealing with isometric or periodic muscular contractions [21]. More specifically, for each subject, the EMG signals of the flexor carpi radialis are segmented in non-overlapping windows of length $w =$ 10 s. This procedure is motivated by the fact that the fatigue insurgence through time is subject-dependent and cannot be standardized a priori among subjects. The MDF is the frequency that splits the EMG power spectrum $P_w(j)$ into two parts with equal power [22]:

$$\mathrm{MDF} = \frac{1}{2}\sum_{j=1}^{J} P_w(j) \tag{2}$$

where J is the length of the frequency bin, and the power spectrum $P_w(j)$ is evaluated on each temporal window w of the EMG signal. In order to identify two levels of fatigue, the MDF values are all normalized of the MDF value obtained in the first temporal window. Then, a range of variation is computed by subtracting the normalized MDF value of the last temporal window from the normalized MDF value of the first temporal window. Finally, the two levels of muscular fatigue are identified as follows. The temporal epoch where the MDF normalized values lie above the 50 % of the MDF range is recognized as low effort, the temporal epoch where the MDF normalized values fall below the 50 % of the MDF range is marked as high effort.

The last step consists in classifying the levels of effort from the set of acquired SC signals. The classification is implemented only on SC, through the k-Nearest Neighbors (k-NN) ML algorithm. In detail, the input of the k-NN algorithm is the sample of normalized SC amplitude $x_{norm}(n)$ of Equation (1), while the output is a binary value of low effort or high effort. Screening the entire sequence x_{norm}, its samples are labelled as low effort or high effort, depending on the temporal epochs defined by the MDF of EMG power spectrum computed according to Equation (2). Figs. 2 and 3 illustrate two examples of MDF curves. In the case of Fig. 2 (a man), by following the procedure described above, the high physical effort appears at 180 s, which represent the last part of acquisition. Differently, in the case of Fig. 3 (a woman), the high physical effort already arises since the first 20 s. Figs. 4 and 5 show, instead, the corresponding acquired SC signals, normalized of their maximum value. Therefore, the trend of MDF curves displays that the fatigue insurgence is dissimilar among subjects. Analogously, the same conclusion can be drawn by observing the trend of normalized SC signals.

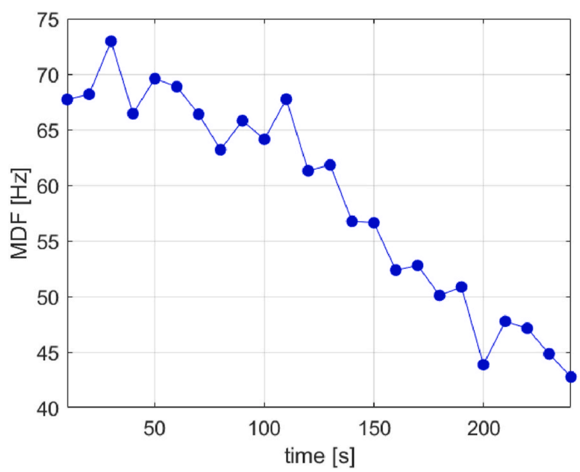

Fig. 2. MDF curve of a man (subject 1) computed on EMG power spectrum: the high physical effort appears at 180 s.

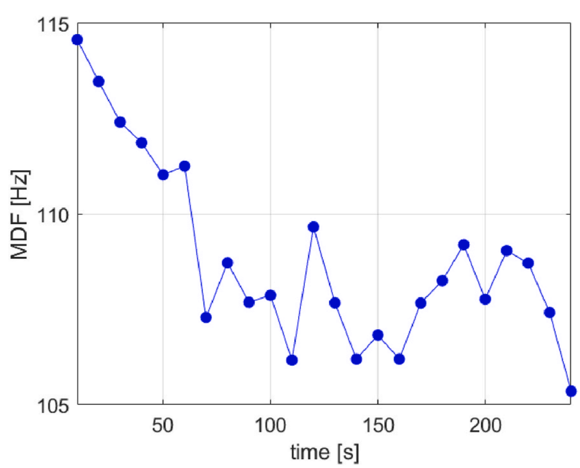

Fig. 3. MDF curve of a woman (subject 2) computed on EMG power spectrum: the high physical effort appears at 20 s.

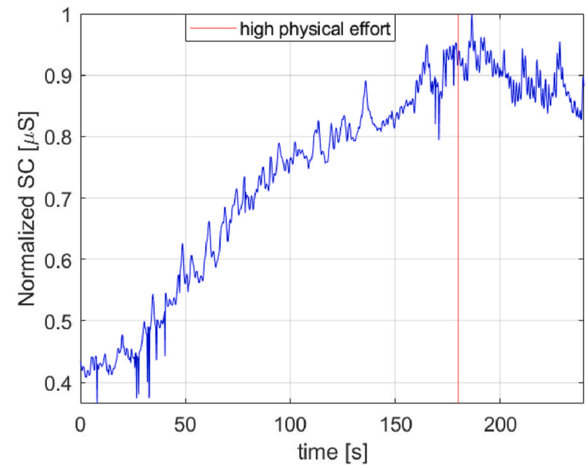

Fig. 4. SC signal of a man (subject 1) with normalized amplitude: the red line represents the beginning of high physical effort determined by MDF curve.

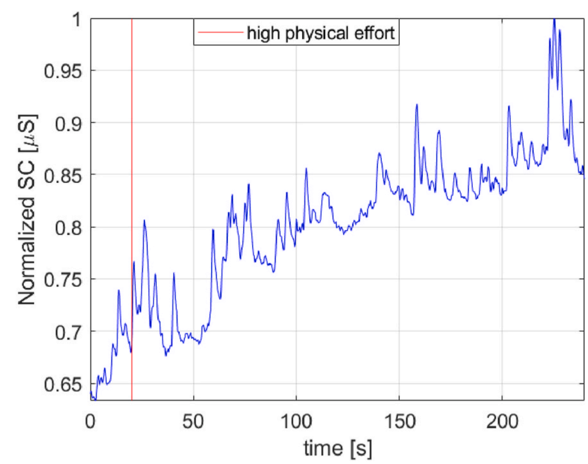

Fig. 5. SC signal of a woman (subject 2) with normalized amplitude: the red line represents the beginning of high physical effort determined by MDF curve.

3. Experimental results

All the three steps consisting in extraction of SC amplitude, identification of the two levels and classification of physical effort are implemented in MATLAB environment. The single signal acquired for each monitored subject consists of $\Delta f_{SC} = 960$ samples. Therefore, the overall dataset contains $N = 5760$ values of normalized SC amplitude. In particular, 70% of dataset is employed for training and validation, while the remaining 30% is used for testing. Moreover, the Euclidean distance is considered for the k-NN implementation.

3.1. Test implementation

The proposed method is analyzed by means of metrics derived from the confusion matrix, and commonly used for performance assessment in ML [23]. These metrics are the following:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}\,100\% \tag{3}$$

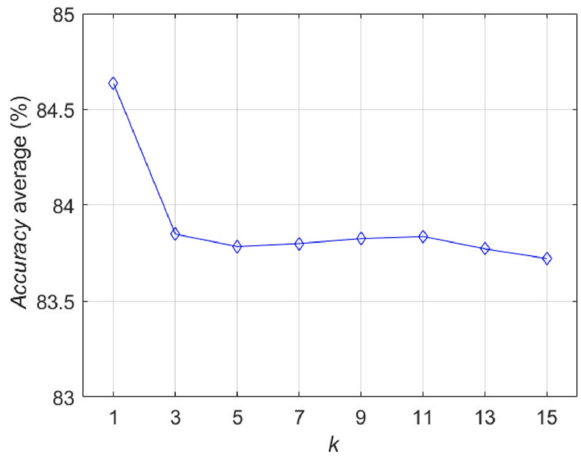

Fig. 6. Average of *Accuracy* versus *k* obtained for 50 random trials.

$$Sensitivity = \frac{TP}{TP + FN}\ 100\% \tag{4}$$

$$Precision = \frac{TP}{TP + FP}\ 100\% \tag{5}$$

$$F_1 = \frac{2\ TP}{2\ TP + FP + FN}\ 100\% \tag{6}$$

where *TP* and *TN* represent, respectively, true positives and true negatives, i.e., the events correctly assigned to their classes, while *FP* and *FN* represent false positives and false negatives, namely, the misclassified events. Worth noting is that, in the ML field, *Accuracy*, *Sensitivity* and *Precision* assume a different meaning from the corresponding terms defined by the International Vocabulary of Metrology (VIM) [24].

3.2. Performance analysis

In a preliminary analysis, *Accuracy* (3) of classification is evaluated depending on different values *k* of the *k*-NN algorithm: $\{1; 3; 5; 7; 9; 11; 13; 15\}$. The values of normalized SC amplitude are randomly selected from the overall dataset to compose a training set and a testing set. The *Accuracy* (3) is evaluated for 50 random trials. Fig. 6 illustrates the corresponding values obtained on average. This analysis shows that the averaged values are characterized by a decreasing trend at the increase of the value *k*. Hence, the value $k = 1$ is set in the *k*-NN algorithm for the consequent analysis.

In order to assess the performance of the proposed approach item by item, the four metrics introduced in the previous Subsection 3.1 are then evaluated: *Accuracy* (3), *Sensitivity* (4), *Precision* (5) and F_1 (6). This time, the metrics are averaged over 100 random trials. In detail, the values of *TP*, *FN*, *FP* and *TN* obtained on average are reported in the confusion matrix of Fig. 7. Fig. 7 clearly demonstrates the good percentage of correct predictions. Finally, for a more comprehensive analysis, Table 1 displays the results of the proposed approach in terms of the common ML metrics [23]. Generally, all the four metrics exhibit good performance, always far beyond the 80%. In particular, the value of *Accuracy*, which is the most common classification metric, reaches on average the value of 84.68%. This value is particularly encouraging. Indeed, SC signals (and, consequently, the corresponding extracted features) are in general not simply weak in amplitude, but also variable in inter-subject and intra-subject studies. In this case, instead, such a result is comparable to the values of *Accuracy* obtained by literature methods based on the extraction of EMG features [25,26], proving the efficacy of the method to evaluate physical effort.

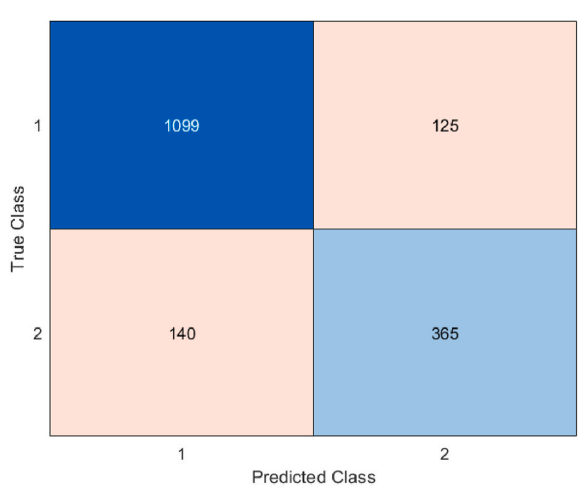

Fig. 7. Confusion matrix of the proposed approach.

Table 1
Classification results obtained on average for the dataset of acquired signals.

Accuracy (%)	*Sensitivity* (%)	*Precision* (%)	F_1 (%)
84.68	89.75	88.74	89.24

4. Conclusions

In this paper, an approach has been proposed to evaluate physical effort by IoT-based wearable sensors. The proposed approach jointly employs wearable SC and EMG sensors. The use of EMG sensor is intended uniquely as a reference to discriminate between low effort and high effort. The two phases of feature extraction and classification are, instead, entirely entrusted to the SC signal alone. More specifically, the proposed approach exploits as feature the normalized SC amplitude. Then, the classification has been implemented through the *k*-NN algorithm.

The experimental tests have been carried out for assessment of fatigue felt by arms, following isometric muscular contractions. The obtained results show good performance in terms of *Accuracy*, *Sensitivity*, *Precision* and F_1. In detail, the values of *Accuracy* and *Sensitivity* reach, respectively, 84.68% and 89.75%. Future work will be intended to investigate different classification algorithms and increase the number of monitored subjects.

Acknowledgements

This research has received funding from the project Vitality – Project Code ECS00000041, CUP I33C22001330007 - funded under the National Recovery and Resilience Plan (NRRP), Mission 4 Component 2 Investment 1.5 - Creation and strengthening of "innovation ecosystems", construction of "territorial leaders in R&D" – Innovation Ecosystems - Project "Innovation, digitalization and sustainability for the diffused economy in Central Italy – VITALITY" Call for tender No. 3277 of 30/12/2021, and Concession Decree No. 0001057.23-06-2022 of Italian Ministry of University funded by the European Union – NextGenerationEU.

References

[1] F.C. Bull, S.S. Al-Ansari, S. Biddle, et al., World Health Organization 2020 guidelines on physical activity and sedentary behaviour, Br. J. Sports Med. 54 (2020) 1451–1462.
[2] A.K. Chowdhury, D. Tjondronegoro, V. Chandran, J. Zhang, S.G. Trost, Prediction of relative physical activity intensity using multimodal sensing of physiological data, Sensors 19 (2019) n° 4509.
[3] A. Ashrant, G. Ali, B. Becerik-Gerber, Monitoring fatigue in construction workers using physiological measurements, Autom. ConStruct. 82 (2017) 154–165.
[4] P. Daponte, L. De Vito, G. Iadarola, F. Picariello, ECG monitoring based on dynamic compressed sensing of multi-lead signals, Sensors 21 (n° 21) (2021).

[5] R. Inaba, S. Yamakawa, T. Kanamoto, et al., Measurement of various intensities of physical activities and categorization of "Locomotive" and "Household" activities provide a subject-specific detailed assessment, Sci. Rep. 11 (2021) 22104.
[6] L. Zhang, M. Diraneyya, J. Ryu, C. Haas, E. Abdel-Rahman, Jerk as an indicator of physical exertion and fatigue, Autom. ConStruct. 104 (2019).
[7] A.S. Oestergaard, N. Gupta, T.F. Smidt, L.F. Sandal, K. Søgaard, The objectively measured physical work demands and physical capacity of offshore wind technicians: an observational field study, Appl. Ergon. 102 (2022) 103716.
[8] Empatica. https://www.empatica.com/.
[9] F. Scardulla, G. Cosoli, S. Spinsante, A. Poli, G. Iadarola, R. Pernice, A. Busacca, S. Pasta, L. Scalise, L. D'Acquisto, Photoplethysmograhic sensors, potential and limitations: is it time for regulation? A comprehensive review, Measurement 218 (2023).
[10] D. Arvidsson, J. Fridolfsson, M. Börjesson, Measurement of physical activity in clinical practice using accelerometers, J. Intern. Med. 286 (n° 2) (2019) 137–153.
[11] E.V. Lambert, G.A. St Clair, T.D. Noakes, Complex systems model of fatigue: integrative homoeostatic control of peripheral physiological systems during exercise in humans, Br. J. Sports Med. 39 (2005) 52–62.
[12] J.F. Tornero-Aguilera, J. Jimenez-Morcillo, A. Rubio-Zarapuz, V.J. Clemente-Suárez, Central and peripheral fatigue in physical exercise explained: a narrative review, Int. J. Environ. Res. Publ. Health 19 (n° 7) (2022).
[13] S. Anwer, H. Li, M.F. Antwi-Afari, W. Umer, A.Y. Wong, Evaluation of physiological metrics as real-time measurement of physical fatigue in construction workers: state-of-the-art review, J. Construct. Eng. Manag. 147 (n° 5) (2021).
[14] G. Iadarola, S. Meletani, F. Di Nardo, S. Spinsante, A new method for sEMG envelope detection from reduced measurements, in: IEEE International Symposium on Medical Measurements and Applications, 2022, pp. 1–6.
[15] C. Tronstad, M. Amini, D. Bach, Ø. Martinsen, Current trends and opportunities in the methodology of electrodermal activity measurement, Physiol. Meas. 43 (2) (2022).
[16] D. Bari, M. Rammoo, H. Aldosky, M. Jaqsi, Ø. Martinsen, The five basic human senses evoke electrodermal activity, Sensors 23 (19) (2023).
[17] G. Iadarola, A. Poli, S. Spinsante, Reconstruction of galvanic skin response peaks via sparse representation, in: IEEE International Instrumentation and Measurement Technology Conference, 2021, pp. 1–6.
[18] G. Iadarola, A. Poli, S. Spinsante, Compressed sensing of skin conductance level for IoT-based wearable sensors, in: IEEE International Instrumentation and Measurement Technology Conference, 2022, pp. 1–6.
[19] G. Iadarola, V. Bruschi, S. Cecchi, N. Dourou, S. Spinsante, Low-cost monitoring for stimulus detection in skin conductance, Acta IMEKO 12 (3) (2023) 1–6.
[20] R.I. Hamilton, A.A. Garcia, J. Bowd, et al., Utilising electrodermal activity sensor signals to quantify nociceptive response during movement activities, BMC Res. Notes 17 (n° 36) (2024).
[21] P.V. Komi, P. Tesch, EMG frequency spectrum, muscle structure, and fatigue during dynamic contractions in man, Eur. J. Appl. Physiol. Occup. Physiol. 42 (1) (1979) 41–50.
[22] A. Phinyomark, P. Phukpattaranont, C. Limsakul, Feature reduction and selection for EMG signal classification, Expert Syst. Appl. 39 (8) (2012).
[23] T. Fawcett, An introduction to ROC analysis, Pattern Recogn. Lett. 27 (8) (2006) 861–874.
[24] Joint Committee for Guides in Metrology, International Vocabulary of Metrology – Basic and General Concepts and Associated Terms (VIM), 2012.
[25] J. Wang, S. Sun, Y. Sun, Recognition of muscle fatigue status based on improved wavelet threshold and CNN-SVM, IEEE Access (2020).
[26] J. Wang, S. Sun, Y. Sun, A muscle fatigue classification model based on LSTM and improved wavelet packet threshold, Sensors (2021).

Grazia Iadarola*, Alessandro Mengarelli, Sandro Fioretti, Susanna Spinsante
Department of Information Engineering, Polytechnic University of Marche, Ancona, Italy

* Corresponding author.
E-mail address: g.iadarola@staff.univpm.it (G. Iadarola).