Joint compression of EEG and EMG signals for wireless biometrics

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***Abstract*—In this paper, we propose a new method for jointly compressing EEG and EMG biosignals based on the so-called cortico-muscular coherence, a function that takes into account the simultaneous frequency changes of the brain and the muscles activity, and can be used, e.g., to classify different kinds of movement. It is shown that this method increases the achievable compression rate compared to transmitting EEG and EMG samples separately, while trading-off with the accuracy of the classification. This can be exploited in several kinds of life and health applications e.g., motor rehabilitation and drivers attention monitoring; it could be especially useful for low-power wireless technologies, such as Bluetooth Low Energy or IEEE 802.15.6, whose transmission resources are limited.**

***Index Terms*—IoT, EEG, EMG, cortico-muscular coherence, haptics, wireless body sensor networks.**

I. Introduction

Wireless body area sensor networks (WBASN) [1] and IoT-health platforms [2] are increasingly exploited to pervasively monitoring e.g., at-risk elderly patients, athletes, and car drivers.

For these kinds of applications, heterogeneous sensors are often included to acquire *vitals*, i.e., biosignals that describe the individual's health condition, environmental measurements, e.g., temperature and humidity, and event information, e.g., emergency alarms and person fall detections.

The collection of such data should be performed through cost-effective and light-weight wireless technologies that are typically limited in terms of transmission capacities, range, and energy efficiency. For example, a typical system provided with 10 electroencephalografic (EEG) channels and 8 bipolar electromyographic (EMG) channels (to simultaneously monitor the brain and 4 muscles) generates a constant bitrate of 800 kbit/s [3] [4]. This data flow, combined with that generated by other sensors, may easily exceed the transmission capabilities of low-power wireless technologies, such as Bluetooth Low Energy [5], IEEE 802.15.6 [6] or LoRa [7], or anyway dramatically shorten the battery lifetime.

In this paper, we challenge this problem by investigating novel techniques to jointly reduce the dimensionality of EEG and EMG signals, while preserving the features that may be significant for the recognition of specific problems or situations.

Several successful algorithms have been already proposed for signals compression of EEG and EMG (separately). For example, commonly used compression algorithms like Set Partitioning In Hierarchical Trees (SPIHT) [8] and Joint Photographic Experts Group J2K standard (JPEG2000) [9] have been adapted to EEG, ECG, and other biosignals achieving good performance [10]. A scalable and energy efficient EEG compression scheme based on discrete wavelet transform (DWT) has been proposed by [11]; finally, compressive sensing techniques have also been tested with EEG [12] [13]. However, the joint compression of heterogenous signals, particularly EEG and EMG, is still missing a deep investigation. To our knowledge, only one recent contribution implemented a deep learning algorithm for jointly compressing EEG and EMG signals in the context of emotions recognition [14].

In this paper, we propose a new algorithm for jointly compressing EEG and EMG data. The rationale is based on the well-known concept of *cortico-muscular coherence* (CMC). Specifically, CMC is defined as the coherence function between the EEG and EMG signals that has been well-characterized in neurophysiology by several studies [15], in both healthy subjects as well as patients affected by different kinds of motor-related diseases. The CMC function accounts for the amount of synchronization between the brain and muscular activity at each frequency, and strongly depends on the particular motor task performed by the individual, e.g., precision grips (fine hand movements), stable (*isometric*) contractions, or rapid muscle contractions [16] [17] [18]. Therefore, the joint processing of EEG and EMG signals can provide useful information to quantitatively describe motor activities. The aim of this work is to show that transmitting the CMC samples over a network, rather than the EEG and EMG signals separately, can significantly reduce the required transmission resources, while keeping a good level of accuracy in the classification of motion activities.

The paper is organized as follows. Section II explains the computation of the CMC and describes the newly proposed algorithm for joint EEG-EMG compression. Section III presents a possible use case and the performance metrics used to evaluate the proposed method. Section IV shows some relevant results and, finally, Section V concludes the paper with a discussion about this contribution and its future developments.

II. Methods

A. CMC computation

In our approach, a simple and widely-used processing pipeline for EEG and EMG signals is considered: each signal is segmented into *trials* of the same duration (typically few seconds), a pass-band filter is applied to each of them

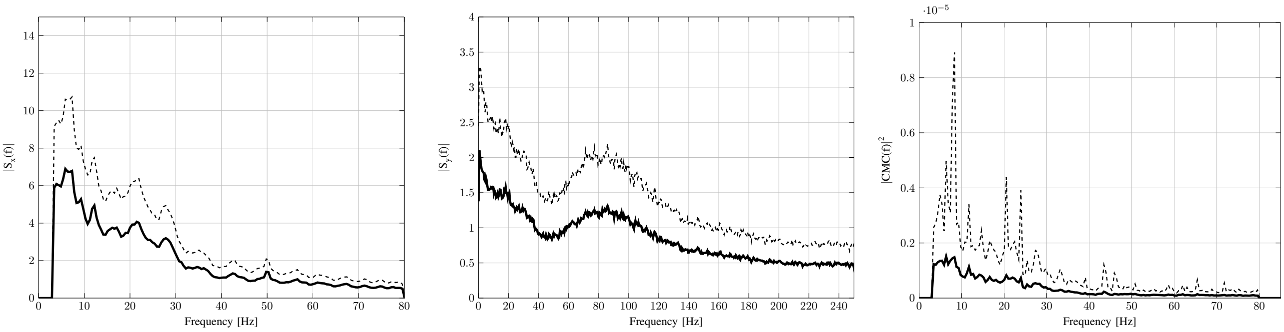


Fig. 1: Example of average power spectra from artefact-free segments of EEG and EMG. (a) $S_x(f)$, (b) $S_y(f)$ and (c) $|CMC(f)|^2$. Solid line represents the mean spectrum, dashed line the sum (at each frequency) of the mean spectrum with the standard deviation spectrum.

to remove frequency content outside the range of interest (3-80 Hz) and, finally, artefacts rejection over all segments is performed. Signal processing is fully implemented in Matlab using our own code. Every EMG trial is further (full-wave) rectified and its envelope is extracted [4].

Then, the computation of CMC is performed, segment by segment, following well-established techniques [19] [20].

Suppose to have N segments available for the CMC estimation, the power spectrum of each of them is firstly computed by means of the Fast Fourier Transform (FFT) algorithm (typically with a frequency resolution of 1 Hz or below). We call $S_x^{(i)}(f)$ and $S_y^{(i)}(f)$ the power spectra of the i-th trial extracted from the EEG and EMG signals, respectively.

Then, $S_x(f)$ and $S_y(f)$ represent the average power spectra taken among all segments of EEG and EMG, respectively.

On the other hand, the cross-correlation function between corresponding EEG and EMG segments is computed and FFT-transformed to get the cross-power spectrum of that trial, $S_{xy}^{(i)}(f)$.

Then, the magnitude square of the CMC of each trial is computed as

$$|CMC^{(i)}(f)|^2 = \frac{|S_{xy}^{(i)}(f)|^2}{S_x^{(i)}(f)S_y(f)}. \qquad (1)$$

As per the Cauchy-Schwarz inequality, it holds

$$0 \leq |S_{xy}^{(i)}(f)|^2 \leq S_x^{(i)}(f)S_y^{(i)}(f), \qquad (2)$$

then every $|CMC^{(i)}(f)|^2$ can be seen as the normalized cross power spectrum between EEG and EMG.

Finally, the $|CMC^{(i)}(f)|^2$, with $i = 1, 2, ..., N$, are averaged to obtain the (magnitude square) CMC estimation, $|CMC(f)|^2$.

$|CMC(f)|^2$ assumes values between 0 and 1, with 1 indicating perfect linear dependence between the two signals.

An example of typical $S_x(f)$, $S_y(f)$ and $|CMC(f)|^2$ spectra is reported in Fig. 1.

As in the case of EEG, CMC spectrum can be also divided into (sub-)bands of interest; we used the following eight (standard) frequency bands [21]: low-α (6-8 Hz), α (8-12 Hz), low-β (13-20 Hz), high-β (20-30 Hz), β (13-30 Hz), low-γ (30-60 Hz), high-γ (60-80 Hz) and γ (30-80 Hz).

B. *Compression*

The joint information between EEG and EMG, i.e., the CMC spectrum, $|CMC(f)|^2$, is computed as a first step in the compression pipeline.

Then, (uniform) quantization of the CMC spectrum is applied. The number of levels (L) is varied in the set $\{2, 4, 8, 16, 32, 64, 128, 256, 512, 1024\}$ using a binary coding of each level, so that 1 to 10 bits are used to define each level. The range of the quantizer is set to $[0, 1]$.

A compression ratio (CR) is defined at this step by the ratio between the number of bits of the original signal segment (typical bit resolution is $b = 12$) and the number of bits of the compressed segment.

Huffman coding [23] or another kind of source coding can be later applied on the output of the quantizer in order to further optimize the bitrate to transmit.

III. Classification and Performance Measurement

In order to prove the efficiency of the newly proposed joint EEG-EMG compression method, an application scenario has been selected: the classification of different kinds of objects during thumb-index holding (i.e., precision grip) of the object itself at a certain height (i.e., without support for the wrist).

We employed the publicy-available dataset *WAY-EEG-GAL* provided within the framework of the European WAY (Wearable interfaces for hand function recovery grasp-and-lift) project [24]. The dataset consists in a set of simultaneous EEG and EMG measurements during a grasp-and-lift task. At each repetition (*trial*), the participant was asked to grasp an object with their thumb and index finger (precision grip), to lift it until a predetermined position, to hold it at that point for at least 2 s (see Fig. 2) and then release the object.

The object was unexpectedly modified in its weight (light = 165 g, medium = 330 g, heavy = 660 g), surface friction (sandpaper, suede, silk) or both, according to a random pattern. In particular, the dataset used in this work counts 84 trials for the light condition, 57 for the heavy condition, 51 for the sandpaper condition and 221 for the silk condition.

During the acquisition, 32 EEG channels were used, with the electrodes located at standard locations (following the *International 10-20 EEG System*) on the participant

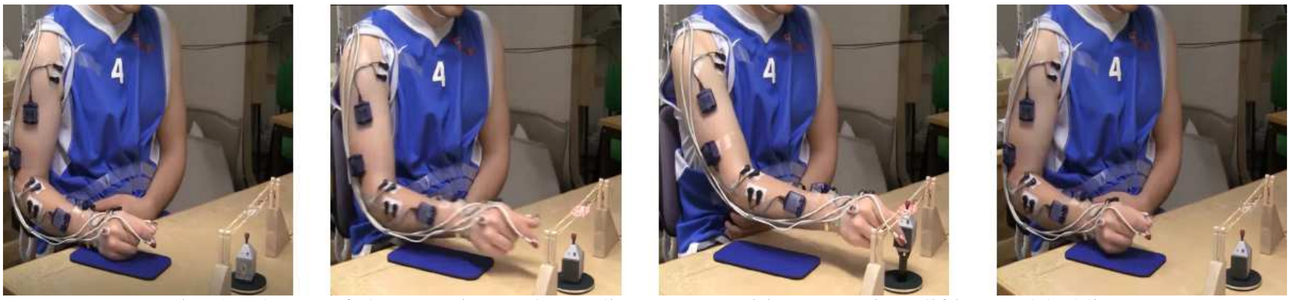


Fig. 2: Phases of the experimental paradigm: rest position, grasping, lifting and holding and releasing (modified from [24]).

scalp. Simultaneous bipolar EMG recording of five different muscles (respectively labelled as AD, BR, FD, CED, FDI) was also performed. Both EEG and EMG signals were downsampled to 500 Hz sampling frequency and the effective bit resolution is 12 bit.

Only data from subject 7 are used in this paper, since experimental records (available online) ensured that the full experimental session was correctly completed.

EEG and EMG segments are extracted from the central period of the sustained contraction to hold the object. Every EEG segment is filtered in the frequency band (3-80 Hz) by means of a Chebyshev type I filter [22] and every EMG segment in the frequency band (3-250 Hz) by means of another Chebyshev type I filter. We consider four different durations for the segmentation: 1, 2, 4 or 6 s. Then, every EMG trial is further (full-wave) rectified.

All EEG and EMG segments (of any duration) that are assessed to be artefact-free (by expert visual inspection) are included in the next compression and classification analysis.

In particular, we denoted as *heavy* trials those where the object weight was 660 g and as *light* trials those with weight of 165 g, irrespective of the surface friction type. Similarly, the *sandpaper* class is constituted by all trials where the object surface was made by sandpaper, and the *silk* class where the object surface was made of silk. Clearly, the heavy and light classes are disjoint, so as the sandpaper and silk classes, while some tasks can be cross-shared by classes of different kinds (e.g., heavy and silk).

Then, a binary linear supervised classifier (a support vector machine with linear kernel) is employed to distinguish among (i) light/heavy objects or (ii) sandpaper/silk surface frictions.

As features for the classification, the set of mean values obtained from $|CMC(f)|^2$ in each frequency band of the range of interest (see Section II-A) is used.

As a comparison, all samples from $S_x^{(i)}(f)$ and $S_y^{(i)}(f)$ are used to classify the same task, taking advantage of the use of all available samples.

The performance of the classification are assessed in terms of accuracy.

IV. Results

First, we confirm that the CMC has the expected frequency distribution, i.e., the largest power values at the lowest frequencies, ensuring the reliability of the preprocessing step and the computation of the CMC [17].

Then, the CMC is uniformly quantized with a number of quantization levels that is increased from 4 up to 1024 in order to provide different CRs and to evaluate the relationship between the compression ratio and the classification accuracy.

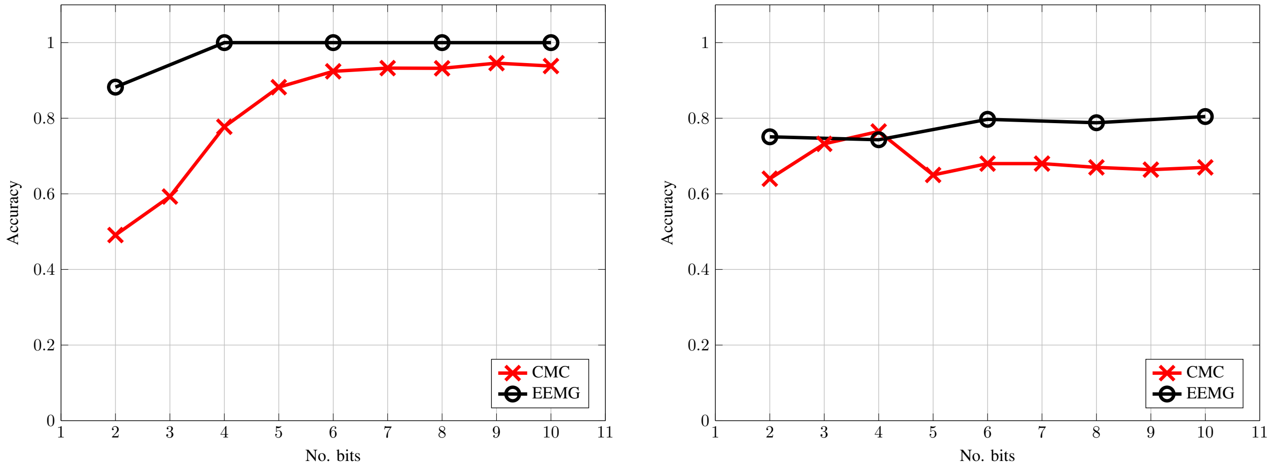
Fig. 3 shows the achievable accuracy with different number of bits, i.e., quantization levels, using the CMC-based features and, as a comparison, the accuracy in case that all EEG and EMG samples are used. The relationship is reported for both the classification of light/healthy trials (Fig. 3 a) and sandpaper/silk trials (Fig. 3 b). In both cases, a duration of 4 s was considered and the C3 electrode (as EEG signal) and the BR muscle (as EMG signal) were selected to compute the CMC.

As expected, the classification accuracy given by the CMC-based features is most often lower or equal than that achievable through the use of all available EEG and EMG samples. However, with a sufficiently large number of bits, i.e., typically greater than 6, the accuracy is remarkably high as compared to a classification using all EEG and EMG samples. Moreover, the results provided by Fig. 3 have to be complemented with the information about the CRs (available in Fig. 5 and described next).

A similar accuracy-quantization behaviour is found also in the cases where another muscle (e.g., FD), another EEG electrode (e.g., CP1, located at the centro-parietal area of the scalp) or a different segment duration (2 s) are considered for the computation of the CMC (Fig. 4). Therefore, the considerations made for the case C3-BR with 4 s can be further extended to other signals of the same dataset and eventually to other datasets where EEG and EMG signals are included.

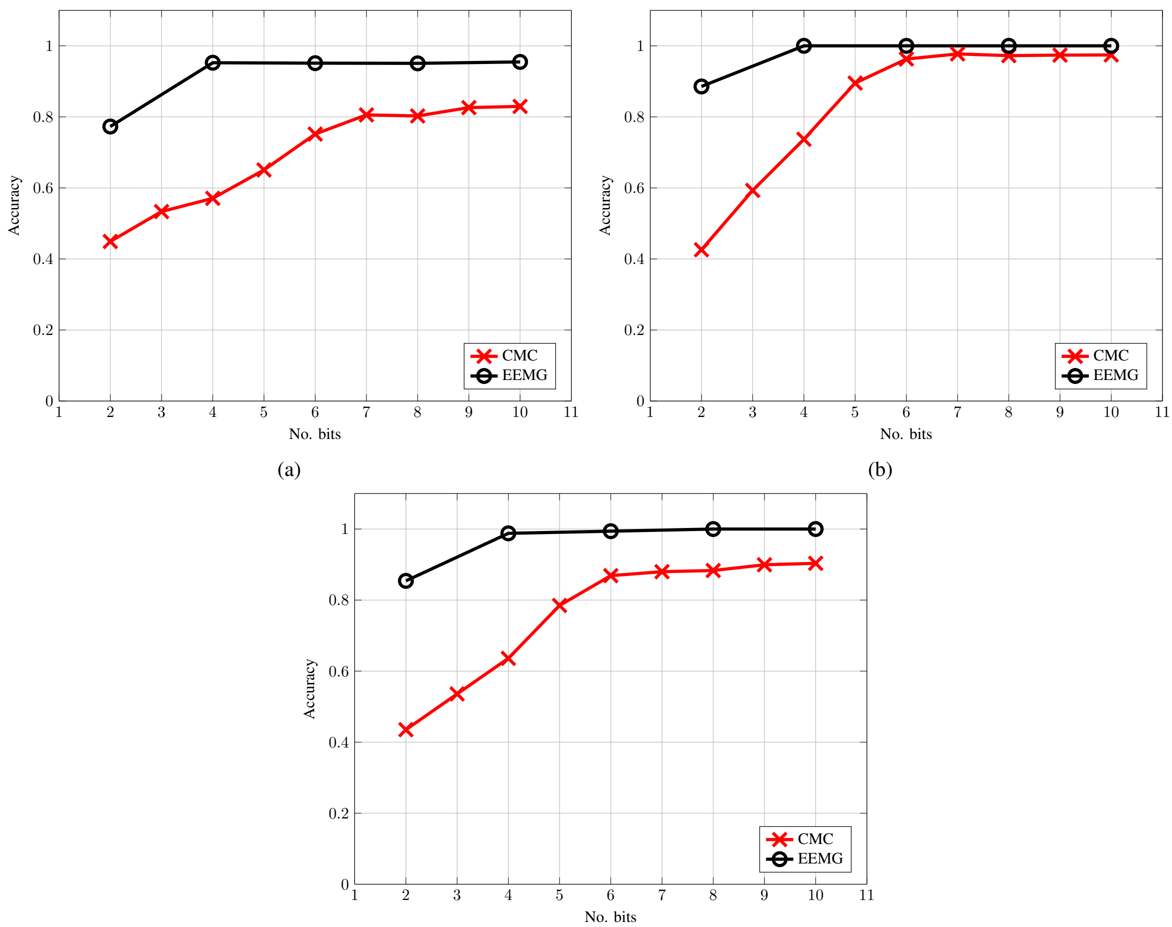
Fig. 5 reports the relationship between the classification accuracy and the CR. A trade-off between the accuracy and the CR can be observed. However, there are specific values for which both accuracy and CR are better in case of CMC-based classification.

For example, when segments have 4 s duration (500 time samples with 12 bits resolution are acquired per second), as shown in Fig. 3a, the CMC-based classification reaches an accuracy of 0.9241 with 6 bits and 8 features (one from each frequency band), while for the classification with the same number of bits using all EEG and EMG samples there are 513 frequency samples in the range (3-80 Hz) and the accuracy approaches 1. In the case of joint compression $CR = 48\text{kbit}/48\text{bit} = 1000$ (30 dB) is obtained; instead, in the case of independent compression of EEG and EMG $CR = 48\text{kbit}/3.078\text{kbit} = 15.59$ (about



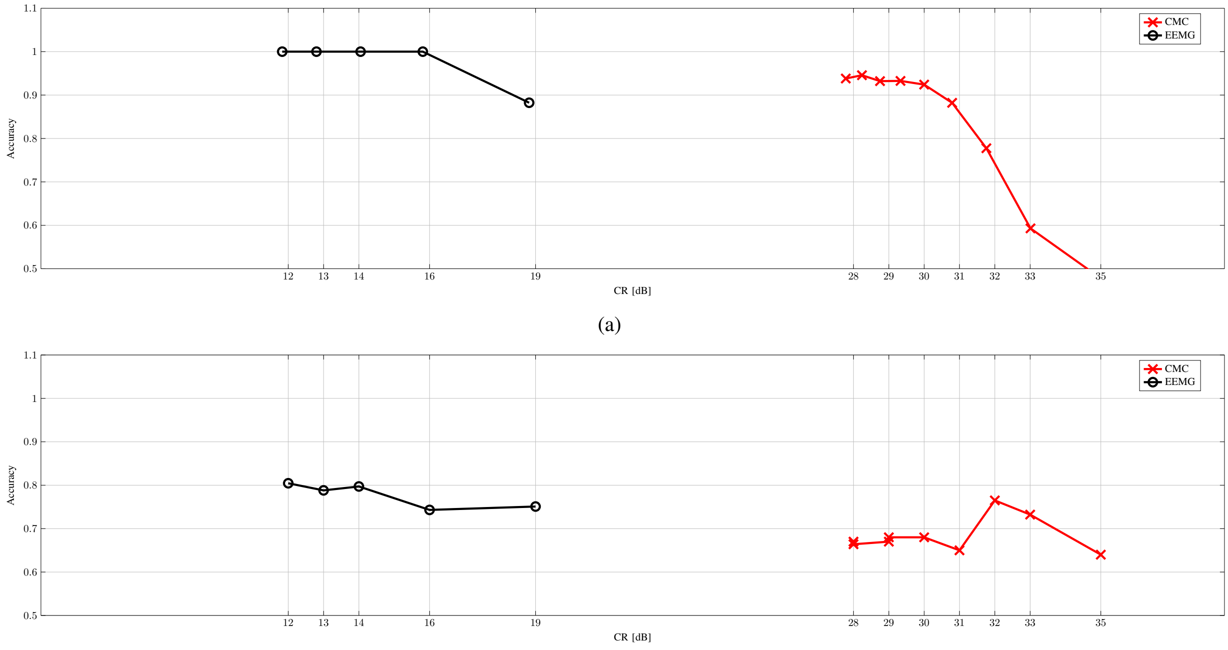
(a) Light/Heavy
(b) Sandpaper/Silk

Fig. 3: Accuracy versus number of quantization levels in case of (a) classification of light/heavy trials and (b) sandpaper/silk trials. For the computation of the CMC we used C3-BR in a period of 4 s). The label *EEMG* stands for the case where all EEG and EMG samples are used for the classification.



(a)
(b)
(c)

Fig. 4: Accuracy versus number of quantization levels for different CMC computations: (a) using a different EMG signal (FD), (b) using a different EEG signal (CP1), (c) using a segments with a different duration (2 s). The label *EEMG* stands for the case where all EEG and EMG samples are used for the classification.



(a)

(b)

Fig. 5: Compression ratio versus accuracy in case of (a) classification of light/heavy trials and (b) sandpaper/silk trials. The label *EEMG* stands for the case where all EEG and EMG samples are used for the classification.

12 dB) is achieved. Therefore, a relevant gain in the CR is provided by the proposed compression algorithm at the expenses of a slight accuracy degradation.

V. Discussion and Conclusions

This work presents a newly developed algorithm for jointly compressing EEG and EMG signals, simultaneously acquired during different kinds of movement. This method acts as a lossy compression in that it considers a few samples of the CMC, i.e., the mean values of CMC at each frequency band of interest, and transmits them, only. A trade-off between accuracy and CR is observed, as expected, with quite high accuracy values for CR values in the range 10 dB to 30 dB (see Fig. 5). From Fig. 5 it can be observed that higher compression ratios can be obtained by jointly compressing EEG and EMG signals, achieving accuracy values that are comparable to those of independent compression of EEG and EMG at lower CRs. This is, for example, the case of compression of weight-related signals (Fig. 5(a)) where joint compression at CRs values of 28 to 30 dB allows to obtain accuracy values above 0.9, while independent compression with $CR = 19$ dB performs worse (accuracy below 0.9).

The joint compression of EEG and EMG signals can be widely employed in those WBASN and IoT-health applications where, i.e., monitoring of daily activities thorugh wearables and lightweight sensors is planned as at-home rehabilitative program for patients suffering from different kinds of neuro-motor pathologies, such as stroke or Parkinson's disease. Indeed, this scenario explains the necessity to have simultaneously recorded EEG and EMG signals from different brain locations and muscles from both limbs.

As far as the authors know, there is only another paper discussing the possibility to jointly compress EEG and EMG [14]. In [14], Said and colleagues used a deep multimodal autoencoders structure to extract discriminant features for classifying different kinds of emotions. They found CRs from 10% up to 90% depending on the complexity of the hidden layers of the multimodal autoencoder (used to integrate EEG and EMG data together). To compare these results with our own, we need to have both results expressed in percentages. Therefore, we compute the new CR values as in [14]: $CR = (1 - m/n) \times 100$, where m is the number of compressed samples and n is the number of samples in the raw signal. Then, we obtain: $CR_1 = (1 - 8/(2 \times 4 \times fs)) \times 100 = 99.80\%$ (for CMC-based lossy compression) and $CR_2 = (1 - 513/(2 \times 4 \times fs)) \times 100 = 87.18\%$ (for EEG and EMG-based lossless compression). Said et al. achieved a maximum accuracy value of 78.1%, instead (provided that they tested their algorithm on a different dataset). We can then conclude that we found better classification accuracies together with comparable CRs, by means of a simpler and less time-consuming compression algorithm.

However, some limitations still affect the present work: first of all, we considered a limited dataset from a single subject performing few specific motor tasks; however, the same algorithm could be further generalized to larger datasets, e.g., with multiple EMG and EEG signals, and to different kinds of signals, e.g., any pair of signals where a common trend or component is present, i.e. the temperature and the relative humidity in an outdoor environment [25] or the heart and the respiratory activities [26]. Second, we considered an uniform quantizer with levels distributed over the entire range of possible values of CMC, i.e., $[0, 1]$. However, a different quantizer, e.g., non-uniform, might be implemented to exploit the granularity of the quantization levels to better match the distribution of the CMC data; similarly, a different kind of classifier could be employed in order to test if better accuracy can be achieved. Finally, a suitable source coding scheme (Huffman, entropy or arithmetic) could be used to code the samples at the output of the quantizer to further optimize the bitrate of the transmitted data.

Nevertheless, in a real-case scenario the joint compression of EEG and EMG signals could be characterized by several challenges: sensors faults, e.g., EEG artefacts, could seriously impact on the CMC computation; therefore, smart and computationally light algorithms for sensors fault real-time detection have to be implemented. Moreover, the energy consumption due to our algorithm needs to be evaluated and compared with other compression algorithms. Here, the trade-off between centralized and distributed computation has to be considered: indeed, in this work we propose a joint compression solution that implies a cooperation between WBASN (heterogeneous) nodes, while in most other cases each single sensor is responsible for digitalization, compression and transmission of biosignals. These two network scenarios have to be properly analyzed in the future based on the specific applications they are required to give solution.

Finally, different kinds of machine learning techniques with particular reference to stacked autoencoders (SAE) [27] and convolutional neural networks (CNN) [28] can be implemented and compared with our CMC-based compression algorithm in order to find the best solution both for compression and classification of heterogeneous biosignals applications.

REFERENCES

[1] G. Z. Yang, "Body Sensor Networks," *Springer Publishing Company*, (II ed.) 2014.

[2] S. M. R. Islam et al., "The Internet of Things for Health Care: A Comprehensive Survey," *IEEE Access*, 2015.

[3] S. Sanei and J. A. Chambers, "EEG signal processing, " *John Wiley & Sons*, 2013.

[4] P. Konrad, "The ABC of EMG: A practical introduction to kinesiological electromyography," vol. 1, 2005.

[5] C. Gomez, J. Oller, and J. Paradells, "Overview and Evaluation of Bluetooth Low Energy: An Emerging Low-Power Wireless Technology," vol. 12, no. 9, pp. 11734–11753, *Sensors* 2012.

[6] IEEE 802.15 WPAN task group 6 body area networks, 2012. Available at: http://standars.ieee.org/findstds/standard/802.15.6-2012.html

[7] L. Vangelista, A. Zanella, and M. Zorzi, "Long-Range IoT Technologies: The Dawn of LoRa," *Springer*, 2015.

[8] Said and Pearlman, "A New, Fast, and Efficient Image Codec Based on Set Partitioning in Hierarchical Trees," *IEEE Trans Circ Sys Video Tech*, vol. 6, no. 3, 1993.

[9] C. Christopoulos, A. Skodras and T. Ebrahimi, "The JPEG2000 still image coding system: an overview," *IEEE Transactions on Consumer Electronics*, vol. 46, no. 4, 2000.

[10] K. Srinivasan, J. Dauwels, and M. R. Reddy, "A two-dimensional approach for lossless EEG compression," *Biomedical Signal Processing and Control*, 2011.

[11] R. Hussein, A. Mohamed, and M. Alghoniemy, "Scalable real-time energy-efficient EEG compression scheme for wireless body area sensor network," *Biomedical Signal Processing and Control*, 2015.

[12] A. Shukla and A. Majumdar, "Row-sparse blind compressed sensing for reconstructing multi-channel eeg signals," *Biomedical Signal Processing and Control*, 2015.

[13] W. Yin, S. Osher, D. Goldfarb, and J. Darbon, "Bregman iterative algorithms for L1-minimization with applications to compressed sensing," *SIAM Journal on Imaging Sciences*, 2008.

[14] Said et al. "Multimodal deep learning approach for joint EEG-EMG data compression and classification," *IEEE WCNC*, 2017.

[15] R. Matsuya, J. Ushiyama, and J. Ushiba, "Inhibitory interneuron circuits at cortical and spinal levels are associated with individual differences in corticomuscular coherence during isometric voluntary contraction," *Sci. Rep.*, 2017.

[16] Baker, Olivier and Lemon, "Coherent oscillations in monkey motor cortex and hand muscle EMG show task-dependent modulation," *J. Physiol.*, 1997.

[17] Mima Steger Schlman Gerloff and Hallett, "EEG measurement of motor cortex control of muscle activity in humans," *Clin. Neurophysiol.*, 2000.

[18] Kilner, Baker, Salenius, Hari and Lemon, "Human cortical muscle coherence is directly related to specific motor parameters," *J Neurosci.*, 2000.

[19] D. Halliday, B. Conway, S. Farmer, and J. Rosenberg, "Using electroencephalography to study functional coupling between cortical activity and electromyograms during voluntary contractions in humans," *Neuroscience Letters*, vol. 241, pp. 5–8, 1998.

[20] Ushiyama et al. "Muscle dependency of corticomuscular coherence in upper and lower limb muscles and training-related alterations in ballet dancers and weightlifters," *J Appl Physiol.*, vol. 109, pp. 1086-1095, 2010.

[21] S. Sanei and J.A. Chambers, "EEG Signal Processing," *Wiley & Sons Ltd*, 2007.

[22] S.K. Mitra and Y. Kuo, "Digital Signal Processing: a computer-based approach," *New York: McGraw-Hill*, vol. 2, 2006.

[23] D. A. Huffman, "A method for the construction of minimum-redundancy codes," *Proc of the IRE*, vol. 40, pp. 1098–1109, 1952.

[24] Luciw et al. "Multi-channel EEG recordings during 3,936 grasp and lift trials with varying weight and friction," *Scientific Data*, 2014.

[25] H.H. Liang and K.T. Huang, "Study on rooftop outdoor thermal environment and slab insulation performance of grass planted roof," *International Journal of the Physical Sciences*, vol. 6, no. 1, pp. 65–73, January, 2011.

[26] D.J. Plews et al. "Comparison of Heart Rate Variability Recording With Smart Phone Photoplethysmographic, Polar H7 Chest Strap and Electrocardiogram Methods," *International Journal of Sports Physiology and Performance*, vol. 12, no. 10, pp. 1324–1328, 2017.

[27] G.E. Hinton and R.R. Salakhutdinov, "Reducing the Dimensionality of Data with Neural Networks," *Science*, vol. 313, pp. 504–507, 2006.

[28] A. Krizhevsky, I. Sutskever and G.E. Hinton, "ImageNet classification with deep convolutional neural networks," *Proc. Advances in Neural Information Processing Systems*, vol. 25, pp. 1090-1098, 2012.