Compression of Biomedical Signals with Mother Wavelet Optimization and Best-Basis Wavelet Packet Selection

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Abstract—We propose a novel scheme for signal compression based on the discrete wavelet packet transform (DWPT) decomposition. The mother wavelet and the basis of wavelet packets were optimized and the wavelet coefficients were encoded with a modified version of the embedded zerotree algorithm. This signal dependant compression scheme was designed by a two-step process. The first (internal optimization) was the best basis selection that was performed for a given mother wavelet. For this purpose, three additive cost functions were applied and compared. The second (external optimization) was the selection of the mother wavelet based on the minimal distortion of the decoded signal given a fixed compression ratio. The mother wavelet was parameterized in the multi-resolution analysis framework by the scaling filter, which is sufficient to define the entire decomposition in the orthogonal case. The method was tested on two sets of 10 electromyographic (EMG) and 10 electrocardiographic (ECG) signals that were compressed with compression ratios in the range 50% - 90%. For 90% compression ratio of ECG (ECG) signals, the percent residual difference after compression decreased from (mean ± SD) 48.6 ± 9.9 % (21.5 ± 8.4 %) with discrete wavelet transform (DWT) using the wavelet leading to poorest performance to 28.4 ± 3.0 % (6.7 ± 1.9 %) with DWPT, with optimal basis selection and wavelet optimization. In conclusion, best basis selection and optimization of the mother wavelet through parameterization led to substantial improvement of performance in signal compression with respect to DWT and random selection of the mother wavelet. The method provides an adaptive approach for optimal signal representation for compression and can thus be applied to any type of biomedical signal.

Index Terms—Wavelet design, wavelet packet, embedded zero-tree.

I. INTRODUCTION

Biomedical signal compression is of increasing interest due to the need of storing or transmitting large amount of multichannel data. The biomedical areas where most compression methods have been developed are medical images, electrocardiogram (ECG), and electroencephalogram (EEG) [6][21]. Since lossless compression is limited to relatively small compression ratios, lossy compression schemes are often implemented. In the latter case, the quality of a compression algorithm is assessed from the distortion rate on the coded signal for a given compression ratio.

Many transform techniques have been previously proposed for biomedical signal compression (e.g., [7][21]). Among these methods, wavelet transform has shown promising results in various areas [5][19]. Discrete wavelet transform (DWT) provides a representation of the signal on coefficients partly localized in time and frequency, is not redundant, and invertible [11]. Processing of the coefficients may allow their representation on a lower number of bits than needed for representing the original signal. The coefficients of the DWT represent the projection of the signal over a set of basis functions generated as translation and dilatation of a prototype function, called mother wavelet. The selection of the mother wavelet determines the signal representation. Many algorithms based on the DWT have been proposed for signal compression. In all cases, however, the mother wavelet is selected from a library of functions or chosen by comparing the results of a few wavelets on a set of experimental signals (e.g., [14][15][19]). However, it is expected that different mother wavelets provide different performance depending on the signal characteristics.

Nielsen et al. [13] recently proposed a compression method based on DWT and embedded zerotree wavelet (EZW) coding in which the mother wavelet was parameterized [10] and optimized with respect to the signal. The optimization criterion was the minimization of the distortion rate in the coded signal for a fixed compression ratio. For electromyographic (EMG) signals, wavelet optimization determined a substantial reduction of the distortion rate with respect to random selection of the mother wavelet.

The DWT represents the signal in a dyadic subband...
decomposition. Generalization of the DWT in wavelet packets allows subband analysis without the constraint of dyadic decomposition. The discrete wavelet packet transform (DWPT) performs an adaptive decomposition of the frequency axis. The specific decomposition (pruned wavelet packet tree) may be selected according to an optimization criterion.

In this study, we propose a novel scheme for signal compression based on DWPT decompositon with optimization of the mother wavelet (after parameterization) and of the basis of wavelet packets. The method is an extension of that previously proposed by Nielsen et al. [13] and is applied to sets of EMG and ECG recordings. The two types of signals chosen for validation of the method provide representative sets of EMG and ECG recordings. The two types of signals previously proposed by Nielsen et al. \[13\] and is applied to

\[\] are computed using low-pass and high-pass filters \( h \) and \( g \) that are directly related to the functions \( \phi \) and \( \psi \). In the case of an orthogonal MRA, the filter \( g \) is deduced from \( h \) from the relation \( g[k] = (-1)^{1-k} h[1-k] \) and the reconstruction filters \( \tilde{h} \) and \( \tilde{g} \) are also deduced from \( h \). Consequently, \( h \) defines the entire MRA.

**Wavelet Packets**

The DWPT generalizes the MRA by decomposing the detail spaces \( W_j \) into two orthogonal subspaces \( W^0_{j+1} \) and \( W^1_{j+1} \) which can be further decomposed into two orthogonal spaces. The resulting basis functions are not only shifts and dilatations of the mother wavelet but also modulated versions of it. Defining \( \psi^0 = \varphi \), \( \psi^1 = \psi \), \( W^0_j = V_j \) and \( W^1_j = W_j \), then \( \{\psi^p_{j,k} = 2^{-j/2} \psi^p(2^{-j} - k)\} \in Z^j \) is an orthonormal basis of \( W^p_j \) \[20\], where

\[
\begin{align*}
\psi^2(t) &= \sqrt{2} \sum_k [h[k]] \psi^0(2t-k) \\
\psi^{2+p}(t) &= \sqrt{2} \sum_k [g[k]] \psi^p(2t-k)
\end{align*}
\]

Eqs. (1) represents the basic stationary wavelet packets and the subspaces verify \( W_j^p = W^p_{j+1} \oplus W^p_{j+1} \). The DWPT of a discrete signal \( (x[k])_{0 \leq k < N} \) is then computed using this discrete sequence as if it was the approximation, belonging to the space \( V_0 \), of a continuous signal:

\[
\begin{align*}
w^0_0[k] &= x[k] \\
w^2_{j+1}[k] &= 2(\tilde{h} \ast w^p_j)[k] & k = 1, \ldots, \frac{N}{2^j} \\
w^{2+p+1}_{j+1}[k] &= 2(\tilde{g} \ast w^p_j)[k]
\end{align*}
\]

with \( \tilde{h}[k] = h[-k] \) and \( \tilde{h}[k] = h[2k] \). The full wavelet packet transform is achieved when \( j = 1, \ldots, \log_2(N) - 1 \). The parameters \( p \), \( j \), \( k \) in

\( w^p_j[k] \) have a natural interpretation as frequency, scale, and position, respectively. This decomposition allows more flexibility than the DWT (deduced from an MRA) in the representation of the signal since the DWPT adaptively segments the frequency axis whereas DWT uses a predefined subband decomposition.

**Wavelet Parametrization**

In both the DWT and DWPT the basis functions are determined by the selection of the mother wavelet. For compression, the mother wavelet is usually chosen within a given library of well-known wavelets (e.g., [5][6][8][14][15][19]). As opposed to this approach, we
propose a signal-based wavelet parametrization to compute DWT and DWPT. The wavelets are parametrized by the scaling filter $h$, which is sufficient to define the DWT and DWPT in the orthogonal case. For a finite impulse response filter of length $L$, there are $L/2 + 1$ conditions to ensure that the wavelets define an orthogonal DWT (or DWPT) and thus there are $L/2 - 1$ degrees of freedom to design the scaling filter $h$. The lattice parameterization described by Vaidyanathan [18] offers the opportunity to design orthogonal wavelet filters via unconstrained parameters. For example, if $L = 6$, the design parameter vector $\theta$ has 2 components $\alpha$ and $\beta$, and $h$ is given by:

$$i = 0,1; h[i] = \frac{1}{4\sqrt{2}}[(1 + (-1)^i \cos \theta + \sin \alpha)(1 - (-1)^i \cos \beta - \sin \beta) + (-1)^i \sin \beta \alpha \cos \alpha]$$

$$i = 2,3; h[i] = \frac{1}{2\sqrt{2}}[(1 + \cos \beta - \alpha \sin \alpha \cos \theta + \sin \alpha \sin \alpha \beta \cos \theta]$$

$$i = 5,6; h[i] = \frac{1}{\sqrt{2}} - h(i - 4) - h(i - 2)$$

The optimal parameter set (i.e., mother wavelet) can be chosen according to a criterion specific for the application. In case of signal compression, a natural criterion is the distortion of the signal after decoding given a compression rate.

**Best Basis Selection in DWPT**

The DWPT decomposition can be seen as a binary tree in which each node represents either a space $W_j^p$ or the related coefficients $C_j^p = \{w_j^p[k]\}_{0 \leq k < N/2^j}$ (Figure 1). This signal representation is highly redundant since each node space is the direct sum of its two children. To obtain a non-redundant and still invertible representation of the signal, the full tree can be pruned by selecting a set of subspaces within the tree. This selection is performed by choosing two children between their parent. The leaves of the resulting tree constitute a decomposition of the initial space $V_0$. For a tree of depth $J$, the number of possible decompositions of $V_0$ is

$$N_J = N_{J-1}^2 + 1$$

This large collection of wavelet packet bases must be explored to find a pertinent basis for a given signal and a given mother wavelet. An exhaustive search is not feasible, given the large number of possible decompositions. Wickerhauser and Coifman [3] proposed a fast algorithm along with an additive information cost function to prune the full wavelet packet tree. A map $M$ from sequences $\{x_i\}$ to $R$ is called an additive information cost function if $M(0) = 0$ and $M(x_j) = \sum_j M(x_j)$. Given such a map, a full wavelet packet tree can be fast pruned [order $O(N \log N)$] to find the basis $B$ that minimizes $M(Bx)$ with a bottom-up series of decisions to keep children nodes (split) or to keep parent node (merge). Numerous additive cost functions are possible. In this paper we compared the following:

- energy entropy: $M(x) = -\sum_j |x_j|^2 \log |x_j|^2$
- $l^1$ norm: $M(x) = \sum_j |x_j|$  
- log: $M(x) = \sum_j \log |x_j|$

For a given cost function, the resulting tree will be different for different mother wavelets. Besides, once selected, the best basis needs to be transmitted from the encoder to the decoder and the inverse transform. This requires at least $\log_2(N_J)$ bits that are added to the output bitstream.

![Fig. 1 A 4-level wavelet packet tree. $W_j^p$ are the projection spaces indexed by scale $j$ and frequency $p$. $V_0$ is the original signal space, as in the multi-resolution analysis.](image)

**Embedded Zerotree Wavelet Packet**

After transforming the signal, the coefficients of the transformation should be coded. The EZW algorithm, first introduced by Shapiro [17], enables to quantize and encode the coefficients of the DWT. This compression algorithm is based on two main concepts: the prediction of the absence of significant information across scale by exploiting self-similarity inherent in the signal, and an entropy-coded successive-approximation quantization (SAQ). This quantization scheme outputs an embedded bit stream by extracting at each step (i.e., each decreasing threshold) another significant bit for each coefficient which has been found to be significant (i.e., with a magnitude superior to the threshold). It allows to stop the compression whenever the desired compression ratio or distortion rate is met.

If a coefficient of the transform is insignificant at a coarse scale, the coefficients at the same temporal position but at a finer scale will likely be insignificant too (zerotree). This assumption yields a parent-child relation between subbands that can be easily extracted from a natural hierarchical subband decomposition, such as the DWT. The concept of zerotree can be extended to the DWPT in order to apply a EZW-like coder to a wavelet packet representation of the signal (EZWP). The extension is done by building a Temporal Orientation Tree [8][16] (i.e., a tree containing the parent-child relations between subbands) for wavelet packet coefficients.
Compression scheme

The overall compression algorithm is separated in two stages. The DWPT of the signal is first computed for a given vector value $\theta$ (mother wavelet parameterization). Then, using a cost function, the wavelet packet tree is pruned according to the best basis algorithm presented above. This stage is lossless and its output is another representation of the signal. However, for transmission purposes, the size of the output of the DWPT is larger than the original number of samples since the tree structure corresponding to the best basis must also be transmitted together with the transformation coefficients. If we assume that each basis is equiprobable, then for $N_J$ possible bases, $\log_2(N_J)$ bits will be needed to code the basis. For example, considering a 12-bit resolution signal of 1024 samples to be compressed with 90% ratio, half of the bits of the resulting compressed signal would be occupied by the basis. To avoid this problem, we restricted the maximum depth of the basis for DWPT to 7. With this choice, 75 bits are needed to transmit the basis while 602 are needed with the maximal depth of 10. Other choices for maximum depth are not tested in this study.

The EZWP block (second stage) encodes the coefficients to achieve a predefined target compression ratio $CR$, defined as:

$$CR(\%) = \frac{Os - Hs}{Os} \cdot 100$$

where $Os$ is the original data size and $Hs$ is the first-order Shannon entropy of the output of the coding block. Hence, an ideal first-order lossless compression is assumed.

The decoding and inverse transformation blocks perform the inverse of these two stages to reconstruct the signal. The distortion metric used to quantify the difference between the original signal $x[k]$ and the reconstructed signal $\hat{x}[k]$ after decoding is the percent residual difference (PRD):

$$PRD(\%) = \frac{\sum_k (x[k] - \hat{x}[k])^2}{\sum_k x[k]^2} \cdot 100$$

Optimisation

DWPT and EZWP are repeated for all values of a predefined set of values of the parameter vector $\theta$ and the $\theta$ value leading to the minimum PRD is chosen as representing the best mother wavelet (wavelet optimization). Thus, in case of DWPT, two signal-based optimization processes are implemented. The first (internal optimization) is the best basis selection that is performed for each mother wavelet, and the second (external optimization) is the selection of the mother wavelet. The coding/decoding scheme for DWPT/EZWP is reported in Figure 2.

Experimental Data

The compression algorithm was tested on two sets of biomedical signals, consisting of surface electromyographic (EMG) and electrocardiographic (ECG) signals recorded from two samples of 10 subjects each. Surface EMG signals were recorded from the upper trapezius muscle of 10 healthy male volunteers (age, mean ± SD, 25.6 ± 2.4 yr). The subjects were in an erect posture with both arms abducted at $90^\circ$. The bipolar electrodes used for recording (Neuroline 720-01-k, Ølstykke, Denmark) were placed 31 mm apart, 20 mm lateral with respect to the mid-point between the acromion and the seventh cervical vertebra. The signals were amplified 2000 times, band-pass filtered (2-500 Hz), digitized on 12 bit and sampled at 1 kHz. Details on data collected can be found in [9].

ECG signals were obtained from the MIT-BIH ECG Compression Test Database [4]. The 10 signals selected to test the compression algorithm were the channel 1 of 08730_01, 11442_01, 11950_01, 12247_01, 12431_01, 12490_01, 12531_01, 12621_01, 12713_01 and 12921_01. Each strip is 4-s long (the first 1024 points of the database signals) and was digitized with the following specifications: 250 samples per second per channel with 12 bit resolution over a ± 10 mV range, bandpass-filtered from 0.1 to 100 Hz to limit analog-to-digital converter saturation and for anti-aliasing (see [12] for details).

Data Analysis

The two sets of signals were compressed with the proposed scheme at compression rates in the range 50-90% (10% increment). The resulting PRD was considered as an index of performance. PRD was compared between DWPT/EZWP with optimized mother wavelet, DWPT/EZWP with classic mother wavelets (Daubechies and Coiflet), DWT/EZW with optimized mother wavelet, and DWT/EZW with classic wavelets. For the DWPT, the three cost functions defined above were compared. For wavelet parameterization, a filter length $L = 6$ was used in all cases, with step size for both parameters of the vector $\theta$ equal to $\pi/7$. Results are reported as mean ± SD over the 10 signals (for each dataset) for signal segments of 1024 samples.
III. RESULTS

EMG signals

Best basis selection and optimal wavelet for a representative EMG recording are shown in Figure 3A. PRD for DWPT/EZWP (using three cost functions for best basis selection) on the 10 EMG recordings is reported in Table 1. Figure 4 shows the results obtained with DWPT/EZWP as compared to those obtained with DWT/EZW. Results from DWT/EZW are presented in detail in [13]. The optimal mother wavelet and the best basis were different among all EMG signals tested.

<table>
<thead>
<tr>
<th>CR(%)</th>
<th>db3</th>
<th>coif1</th>
<th>worst</th>
<th>Optimal</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>4.0 ± 0.7</td>
<td>4.2 ± 0.9</td>
<td>10.9 ± 1.7</td>
<td>3.3 ± 0.6</td>
</tr>
<tr>
<td>60</td>
<td>6.4 ± 1.1</td>
<td>7.1 ± 1.4</td>
<td>16.7 ± 2.2</td>
<td>5.1 ± 0.6</td>
</tr>
<tr>
<td>70</td>
<td>10.8 ± 1.9</td>
<td>10.3 ± 1.3</td>
<td>27.6 ± 4.2</td>
<td>9.0 ± 1.5</td>
</tr>
<tr>
<td>80</td>
<td>18.4 ± 1.9</td>
<td>17.9 ± 2.1</td>
<td>41.8 ± 4.5</td>
<td>15.3 ± 2.5</td>
</tr>
<tr>
<td>90</td>
<td>32.6 ± 3.9</td>
<td>31.5 ± 3.9</td>
<td>60.3 ± 6.5</td>
<td>29.0 ± 2.0</td>
</tr>
</tbody>
</table>

ECG signals

Figure 3B reports an example of best basis selection and optimal wavelet for a representative ECG recording. Tables 2 and 3 show the PRD resulting from DWT/EZW and DWPT/EZWP, respectively. The optimal mother wavelet was different among all ECG signals tested. Moreover, although with a smaller impact on PRD, also the best basis differed among all ECG signals.

<table>
<thead>
<tr>
<th>CR(%)</th>
<th>db3</th>
<th>coif1</th>
<th>worst</th>
<th>Optimal</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>0.9 ± 0.2</td>
<td>0.9 ± 0.2</td>
<td>2.7 ± 1.0</td>
<td>0.8 ± 0.2</td>
</tr>
<tr>
<td>60</td>
<td>1.3 ± 0.5</td>
<td>1.3 ± 0.5</td>
<td>4.0 ± 1.7</td>
<td>1.2 ± 0.4</td>
</tr>
<tr>
<td>70</td>
<td>2.1 ± 0.5</td>
<td>2.2 ± 0.7</td>
<td>6.5 ± 2.9</td>
<td>1.9 ± 0.4</td>
</tr>
<tr>
<td>80</td>
<td>3.6 ± 0.9</td>
<td>3.4 ± 0.8</td>
<td>11.9 ± 5.0</td>
<td>3.0 ± 0.9</td>
</tr>
<tr>
<td>90</td>
<td>7.5 ± 2.8</td>
<td>7.3 ± 2.4</td>
<td>21.5 ± 8.4</td>
<td>6.2 ± 1.4</td>
</tr>
</tbody>
</table>
Tab. 3 Percent residual difference (PRD) (mean ± SD, over the 10 ECG signals) for DWPT/EZWP using Daubechies 3 (db3), Coiflet 1 (coif1), and best/worst parameterized wavelets and three cost functions (energy entropy, log and $l^1$ norm) for best basis selection. The “worst” wavelet is the one leading to the highest PRD among the tested wavelets.

<table>
<thead>
<tr>
<th>CR(%)</th>
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<tbody>
<tr>
<td></td>
<td>Energy Entropy</td>
<td>Log</td>
<td>$l^1$ norm</td>
<td></td>
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<tr>
<td>50</td>
<td>0.8 ± 0.2</td>
<td>1.0 ± 0.3</td>
<td>3.7 ± 1.6</td>
<td>0.7 ± 0.2</td>
</tr>
<tr>
<td>60</td>
<td>1.3 ± 0.4</td>
<td>1.4 ± 0.4</td>
<td>5.9 ± 2.9</td>
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<tr>
<td>70</td>
<td>2.1 ± 0.7</td>
<td>2.2 ± 0.6</td>
<td>9.9 ± 5.4</td>
<td>1.8 ± 0.5</td>
</tr>
<tr>
<td>80</td>
<td>3.8 ± 1.2</td>
<td>4.0 ± 1.4</td>
<td>15.2 ± 6.5</td>
<td>3.2 ± 1.0</td>
</tr>
<tr>
<td>90</td>
<td>9.0 ± 3.5</td>
<td>8.8 ± 4.2</td>
<td>30.6 ± 13.0</td>
<td>7.0 ± 2.0</td>
</tr>
</tbody>
</table>

IV. DISCUSSION

A compression algorithm based on wavelet packets and mother wavelet optimization has been proposed. The algorithm is an extension of the DWT optimization proposed in [13] with the inclusion of the best wavelet packet tree and parameterization of the mother wavelet. The representation of the signal with wavelet packet corresponds to the distribution of signal energy over subbands. The separation between subbands is performed by filters whose selectivities depend on the mother wavelet and whose bandwidths depend on the packet selected. Joint optimization of the mother wavelet and of the wavelet packet corresponds to the optimal subband analysis in terms of filter transfer function and bandwidths for the purpose of compression.

The best basis selection resulted in a further decrease in PRD with respect to DWT for EMG signals. In this case, DWPT with Daubechies and Coiflet wavelets performed better than DWT with optimal wavelet (compare Figure 4 and Table 1), indicating that the best basis for EMG compression is very different from the dyadic wavelet basis (see also Figure 3A). A basis optimization is thus necessary. It is noted that for EMG signals, PRD in case of, e.g., 90% compression ratio was reduced from ~48% with DWT/EZW and the wavelet leading to poorest performance (Figure 4) to ~28% with DWPT/EZWP and optimized wavelet (Table 1), which is a substantial improvement in performance. Table 1 shows that the cost function did not significantly influence the results, thus any of the three cost functions compared can be used.

For ECG signals, the best basis selection in DWPT was less effective than for EMG signals, although all ECG signals resulted in a different best basis. As shown in Figure 3B, the best basis for the ECG signals analysed was close to the dyadic wavelet basis and, due to the need to transmit the basis, the PRD was similar for DWT/EZW and DWPT/EZWP (Tables 2 and 3). Thus, as expected, the gain in performance strongly depended on the signal type. The chosen representative signal sets allow to show different impacts of the two optimization procedures on performance. However, it is underlined that the proposed optimized DWPT/EZWP method does not result in significant worsening of performance even when the optimal basis is close to the dyadic one (the set of ECG recordings chosen in this study). Its application may provide large or more limited improvement over classic DWT depending on the signal type. In particular, the DWPT/EZWP approach with best basis selection performs consistently worse than the DWT/EZW in case of worst wavelet.

Methods comparison

The method proposed (DWPT/EZWP) has been compared with DWT/EZW with classic wavelets, which has been used...
in previous work (e.g., [14][15][19]). We have also shown the improvement in performance due separately to optimization of the mother wavelet and to best basis selection, comparing a number of possible wavelet approaches (Tables 1-3 and Figure 4). Comparison with methods not based on wavelets was not reported since in most cases it is difficult to compare different encoding schemes. For example, the algebraic code excited linear prediction (ACELP) paradigm, widely used for speech signal coding [1] and recently also applied for EMG compression [2], allows only a few choices of compression ratios corresponding to bit rates ranging from 4.75 kb/s to 12.2 kb/s (in the case 12.2 kb/s, the compression ratio is 87.3%). For this reason, the present work focused only on wavelet compression schemes. In addition, the encoder chosen (EZWP) is naturally adapted to the hierarchical DWPT transformation but any other encoding scheme could be used with the proposed optimization. The current study aimed mainly at proposing a subband signal decomposition optimized for the purpose of compression while the specific encoding scheme was of smaller interest.

V. CONCLUSION

In conclusion, it was shown that best basis selection and optimization of the mother wavelet through parameterization lead to improvement of performance in signal compression with respect to random selection of the mother wavelet and DWT. The method provides an adaptive approach for optimal signal representation for the purpose of compression and can thus be applied to any type of one-dimensional biomedical signal.

REFERENCES

audio signals.

Dario Farina graduated summa cum laude in Electronics Engineering (MSc) from Politecnico di Torino, Torino, Italy, in February 1998. During 1998 he was a Fellow of the Laboratory for Neuromuscular System Engineering in Torino. In 2001 and 2002 he obtained the PhD degrees in Automatic Control and Computer Science and in Electronics and Communications Engineering from the Ecole Centrale de Nantes, Nantes, France, and Politecnico di Torino, respectively. In 1999-2004 he taught courses in Electronics and Mathematics at Politecnico di Torino and in 2002-2004 he was Research Assistant Professor at the same University. Since 2004, he is Associate Professor in Biomedical Engineering at the Department of Health Science and Technology of Aalborg University, Aalborg, Denmark, where he teaches courses on biomedical signal processing, modeling, and neuromuscular physiology. He regularly acts as referee for approximately 20 scientific International Journals, is an Associate Editor of IEEE Transactions on Biomedical Engineering, is on the Editorial Boards of the Journal of Neuroscience Methods, the Journal of Electromyography and Kinesiology, and Medical & Biological Engineering & Computing, and member of the Council ISEK (International Society of Electrophysiology and Kinesiology). His main research interests are in the areas of signal processing applied to biomedical signals, modeling of biological systems, basic and applied physiology of the neuromuscular system, and brain-computer interfaces. Within these fields he has authored / co-authored more than 100 papers in peer-reviewed Journals. Dr. Farina is a Registered Professional Engineer in Italy.