Discrimination of Healthy and Post-partum Subjects using Wavelet Filterbank and Auto-regressive Modelling

Rolf Vetter[1], Jonas Schild[1], Annette Kuhn[2] and Lorenz Radlinger[3]
[1]*Institute for Mobile Communication, Bern University of Applied Siences, Jlcoweg 1, Burgdorf, Switzerland*
[2]*Women's Hospital, Urogynaecology, Bern University Hospital and University of Bern, Bern, Switzerland*
[3]*Applied Research and Development Physiotherapy, Bern University of Applied Sciences, Health Bern, Switzerland*

Keywords: Wavelet, Autoregressive Modelling, Patient Discrimination, Pelvic Floor Muscle.

Abstract: Rehabilitation therapies to treat female stress urinary incontinence focus on the reactivation of pelvic floor muscle (PFM) activity. An objective measure is essential to assess a subject's improvement in PFM capabilities and increase the success rate of the therapy. In order to provide such a measure, we propose a method for the discrimination of healthy subjects with strong PFM and post-partum subjects with weak PFM. Our method is based on a dyadic discrete wavelet decomposition of electromyograms (EMG) that projects slow-twitched and fast-twitched muscle activities onto different scales. We used a parametric auto-regressive (AR) model for the estimation of the frequency of each wavelet scale to overcome the poor frequency resolution of the dyadic decomposition. The feature used for discrimination was the frequency of the wavelet scale with the highest variance after interpolation with the nearest neighboring scales. Twenty-three healthy and 26 post-partum women with weak PFM who executed 4 maximum voluntary contractions (MVC) were retrospectively analysed. EMGs were recorded using a vaginal probe. The proposed method has a lower rate of false discrimination (4%) compared to the two classical methods based on mean (9%) and median (7%) frequency estimation from the power spectral density.

1 INTRODUCTION

Involuntary urinary leakage during effort or exertion, such as jogging, coughing or sneezing is often related to insufficient pelvic floor muscle (PFM) function and strength (Bø and Sherburn, 2005). It constitutes an embarrassing condition, which can lead to social exclusion. Modern rehabilitation therapies such as stochastic resonance whole body vibration (Lauper et al., 2009) focus on the reactivation of PFM activity. In such therapies it is necessary to dispose of an objective measure to assess a subject's improvement. Such a measure, when used as direct feedback, could reinforce the efficiency and success rate of the therapy. In an attempt to construct such a measure, we present in this paper a method for the discrimination of healthy subjects with strong PFM capabilities and post-partum subjects with weak PFM capabilities.

In clinical practice, various methods are under investigation for the assessment of PFM capabilities (Bø and Sherburn, 2005). A promising method is based on ElectroMyoGraphy (EMG) signals recorded from surface electrodes embedded on vaginal probes (Bø and Finckenhagen, 2001). This method estimates descriptive statistics of EMG signals to quantify the dynamics and intensity of the PFM activity. Signal variance is often used as an indicator of the muscle contraction intensity while mean or median frequency of the Fast Fourier Transform (FFT) spectrum of the signal is used to quantify the muscle dynamics (Auchincloss and McLean, 2009).

However, it is well established that EMG signals are stochastic and non-stationary with intermittent burst-like activities. Various studies on EMG signals have put forward the superiority of wavelet-based signal analysis over FFT-based methods for handling the burst-like EMG activity (Croce et al., kein Datum) in the frequency range 10-400Hz. Tscharner et al. used 10 non-linearly scaled wavelets to cover this frequency band (Tscharner et al., 2003). In a discrimination application it would be preferable to have a lower number of wavelets for a better capturing of the physiological phenomena under investigation (Vaseghi, 2008). Wavelet scales

Vetter R., Schild J., Kuhn A. and Radlinger L..
Discrimination of Healthy and Post-partum Subjects using Wavelet Filterbank and Auto-regressive Modelling.
DOI: 10.5220/0005176301320137
In *Proceedings of the International Conference on Bio-inspired Systems and Signal Processing* (BIOSIGNALS-2015), pages 132-137
ISBN: 978-989-758-069-7

should be chosen in such a way that signal components related to different physiological phenomena are projected onto different scales. Indeed, it has been shown in numerous biomedical applications that signal separation is an important first step to relevant signal analysis and discrimination (Vetter, 1999).

Urinary continence requires strong and fast muscle contraction (Shishido et al., 2008). Human muscles consist of slow-twitched and fast-twitched muscle fibers and fast contractions with high forces necessitate a larger recruitment of fast-twitched muscle fibers (Guyton and Hall, 2011). To provide optimal signal separation before discrimination we propose in this paper a dyadic discrete wavelet decomposition that projects signal components related to activities of the slow-twitched and the fast-twitched muscles mainly on different scales while simultaneously minimizing the number of scales. This guarantees a minimum of salient features for subsequent discrimination. To overcome the poor frequency resolution of the dyadic decomposition, we use a parametric auto-regressive (AR) model for the estimation of the frequency of each wavelet scale.

2 METHODS

2.1 Subjects and Protocol

Data from a cross sectional study including 49 women (Lauper et al., 2009) was retrospectively analyzed. The study included 23 healthy women with strong PFM capabilities and 26 post-partum women with pelvic floor muscle weakness. In a first step, the PFM‘s weakness was assessed digitally during a maximal voluntary contraction (MVC) in a sitting position and graded according to the Oxford scale (Bø and Finckenhagen, 2001) with six categories: M_0=no contraction, M_1=flicker, M_2=weak, M_3=moderate, M_4=good, M_5=strong. Then, each subject underwent four 5 seconds-MVC split over 2 days (2 each day), during which EMG signals were recorded.

For the discrimination study presented herein, a subset of subjects was selected according to the following criteria: (1) healthy subjects had a grading on the Oxford scale larger than M_4 and (2) weak PFM subjects had a grading on the Oxford scale of maximally M_3. This reduced the original database to 136 recordings. Thirty-four recordings were used for the development phase of the algorithm and the remaining 102 recordings were used for the validation phase. Both, development and validation databases were equilibrated with an equal number of healthy and weak PFM subjects.

2.2 Data Acquisition

The EMG of PFM was obtained from a vaginal probe (Periform, Parsenn-Produkte AG, Switzerland). These EMG signals were recorded using a 16-channel telemetric system (TeleMyo 2400 G2, Noraxon U.S.A. Inc., Scottsdale, AZ, USA). The reference electrode (Ambu Blue Sensor N, Ambu A/S, Ballerup, Denmark) was applied according to the recommendations of SENIAM on the crista iliaca after preparation of the skin (Hermens et al., 2000). The impedance was controlled to be lower than 5 kΩ. The vaginal probe was connected to the transmitter of the telemetric system via a flexible cord with an integrated pre-amplifier (baseline noise: <1 μV RMS; input impedance: >100 MΩ; CMMR: >100 dB; input range: +/−10 mV; base gain: 500; integrated band-pass filter: 10–500 Hz).

Finally, all signals were sampled and recorded at a rate of 1 kHz using a 12-bit analog-digital converter (Meilhaus ME-2600i; SisNova Engineering; Zug, Switzerland) and the software package “ads” (version 1.12, uk-labs, Kempen, Germany).

The EMG signals were visually controlled for artifacts and additionally corrected for baseline offset by high pass filtering with a cut off frequency of 0.1 Hz via ads-software.

2.3 Algorithm Development

2.3.1 Wavelet Transform

The proposed algorithm is based on the hypothesis that there is shift in muscle contraction dynamics between healthy subjects and weak PFM subjects undergoing a MVC protocol measured with EMG signals.

A wavelet approach was chosen in numerous previous studies on EMG due to the non-stationary nature of EMG and their burst-like structure (Tscharner et al., 2003). This is also the approach we chose. In a wavelet transform the signal is locally projected on a scaled and translated wavelet function $\psi_{a,b}(t)$:

$$W_z\ (a,b)=\int_{-\infty}^{\infty} x(t)\psi_{a,b}(t)dt \quad (1)$$

where $a \in R^+$ and $b \in R$ are the scaling and translation parameters. The wavelet function $\psi_{a,b}(t)$ is obtained by translating the mother wavelet scaled by a factor a at the time b, namely

$$\psi_{a,b}(t) = |a|^{-0.5}\psi\{(t-b)/a\} \tag{2}$$

The factor $|a|^{-0.5}$ is introduced to guarantee energy preservation. An analysis of the Equation 2 shows that larger values of a stretch the basic wavelet function and allow the analysis of low-frequency components with low temporal accuracy. In contrast, smaller values of a provide contracted versions of the basic wavelet, which allows the analysis of high frequency components with high temporal accuracy. As a result, wavelets are located both in time and frequency and constitute an important tool for time-frequency analysis.

The free parameters, which have to be chosen for each given application, are the mother wavelet ψ and the range of values for a and b. In EMG analysis, Daubechies, Symlet or Morlet wavelets have shown promising performance due to their resemblance with the burst-like EMG signal structure (Croce et al., kein Datum). We used the Symlet wavelet due to its symmetric structure.

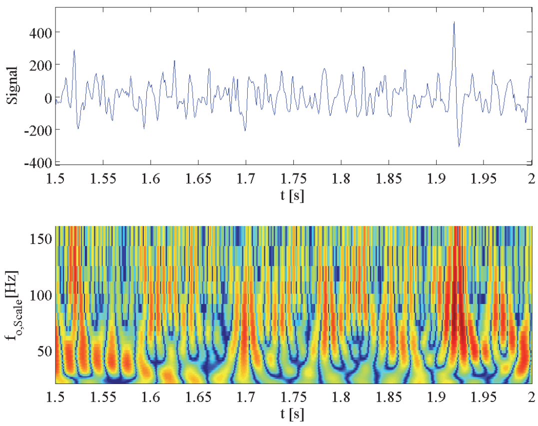

Figure 1: Time signal (top) and CWT (bottom) using Symlet mother wavelet of EMG signals of PFM activity of a healthy subject.

If the scaling and translation parameters a and b are free to take on all values, one obtains the Continuous Wavelet Transform (CWT). Figure 1 shows a typical EMG signal and the associated CWT of EMG signals of PFM activity of a healthy subject. To give a comprehensive representation we used center frequency of the scale instead of scale number as it is usually done. One can clearly distinguish alternating high signal intensities in the scales corresponding to frequency bands below (LF) and above (HF) approximately 60Hz. This observation may be related to an intermittent change in recruitment of sow-twitched and fast-twitched muscle fibers.

The CWT is a tool for visual inspection of data, but provides in the given application poorer performance than a more compact representation, such as the Discrete Wavelet Transform (DWT) based a dyadic choice of the scaling parameter.

Indeed, in biomedical engineering best performance is obtained, when the analysis method mimics as close as possible the phenomenon under investigation (Vetter et al., 1998). Thus phenomena of different origins should be projected onto different wavelet scales. This can be obtained by choosing discrete values for a and b in Equation 1, namely $a_m = 2^m$ and $b_{n,m} = n2^m$ for $n, m = \pm1, \pm2, \pm3, \ldots$ and yields the DWT. The signal $x(t)$ is decomposed on different scales as follows (Akay, 1995):

$$x(n) = \sum_{k\in Z} a_L(k)\,\phi_{2^L}(n-k\,2^L) + \sum_{l=1}^{L}\sum_{k\in Z} d_l(k)\,\psi_{2^l}(n-k\,2^l) \tag{3}$$

where $\psi_{2^l}(n-k2^l)$ are discrete, translated, scaled analysis wavelets and $\phi_{2^L}(n-k2^L)$ are discrete scaling functions. This decomposition splits the signal into low-passed $a_L(k)$ and band-passed detailed signals or wavelet coefficients $d_l(k), l = 1,2,3, \ldots L$. A straightforward implementation of the dyadic DWT can be based on two quadrature mirror filters, a high-pass filter $h(n)$ and a low-pass filter $g(n)$ and appropriate downscaling (Akay, 1995). This whole procedure provides an equivalent filter-bank with transfer functions as shown in Figure 2. By choosing an appropriate sampling frequency of 1 kHz we obtained an ideally suited approach for the analysis of EMG signals from PFM with the corner frequencies of approximately 250 Hz, 125 Hz, 62 Hz and 32 Hz and 16 Hz.

2.3.2 Feature Extraction

From the detailed signal $d_l(k)$ at scale 2^l we extracted salient features through a descriptive statistics related to the intensity of muscle activation. We used in our algorithm signal variance of the detailed signals of the scales $\sigma_l^2, l = 1,2,3, \ldots L$ to quantify contraction intensity as proposed in (Tscharner et al., 2003). Based on the analysis of Figure 1 we supposed that the variances of the detailed signals of scale 2 and 3 (frequency range 62 Hz–256 Hz) was influenced mainly by activation of fast-twitched muscle fibres, whereas variance of scale 4 and 5 was mainly related to the activation of slow-twitched muscle fibres.

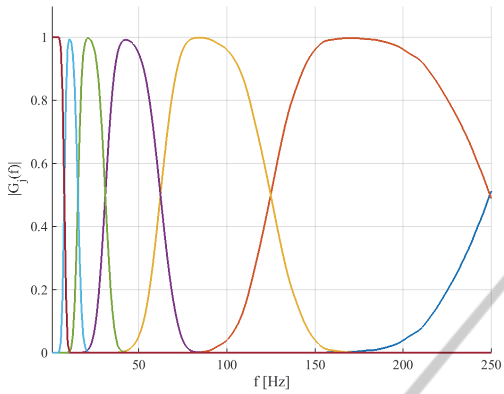

Figure 2: Frequency response of different scales of the dyadic discrete Wavelet Transform.

The quantification of the dynamics of muscle activation is another important aspect, which was extracted from the frequency characteristics of the detailed signals $d_l(t)$. In various EMG studies, interpretation of the wavelet transform in terms of frequency is achieved through a direct mapping using the central frequency of a given scale (Tscharner et al., 2003). This may be appropriate for a wavelet transform with narrowband characteristics. In a dyadic decomposition, the upper bands have larger bandwidths (see Figure 2) which may lead to considerable inaccuracies in terms of frequency mapping.

Therefore we applied an AR modelling and subsequent analysis of root location for the estimation of the frequency of the detailed signals of the different scales $f_{0,l}^2, l = 1,2,3, \dots L$.

Parametric AR modelling is well known for its accuracy in terms of frequency estimation of quasi harmonic oscillations and very efficient algorithms are proposed in literature (Vaseghi, 2008). We applied Burg's algorithm for robust parameter and accurate central frequency estimation. The last step in the development of a discrimination algorithm consists generally in an optimal merging of the extracted features after discarding unreliable features and adequate normalization (Vaseghi, 2008). We tested various approaches to merge the above extracted variance and frequency features of the detailed signals, such as for example neural networks and fuzzy logic. However, the development data base put forward the superiority of a simple quasi maximum likelihood approach. The most important feature was identified though determination of the scale with the highest variance, which provided the scale-index l_{max}. Refined frequency estimation was then obtained by including information of the adjacent scales through classical weighting as follows:

$$f_o = \sum_{l=l_{\max}-1}^{l_{\max}+1} f_{o,l}\, p_l \tag{4}$$

$$p_l = \frac{\sigma_l^2}{\sum_{j=l_{\max}-1}^{l_{\max}+1} \sigma_j^2} \quad \text{for} \quad l = l_{\max}-1, l_{\max}, l_{\max}+1 \tag{5}$$

2.3.3 Statistical Processing and Optimization

The analysis of features extracted from the experimental data showed that MVC signals were highly non-stationary. Subjects were rarely able to achieve maximal voluntary muscle contraction at the same level during 5 seconds. The algorithm had therefore to discard marginal feature values. This was achieved by estimating f_o consecutively on segments of a duration of 1 second with an overlap of 50% and by processing the median of all resulting f_o estimations. The discrimination of healthy and weak PFM subjects was obtained by comparing f_o to a critical value f_{crit}. The proposed algorithm has 3 freely adjustable parameters, which are the mother wavelet, the sampling frequency and the threshold for classification f_{crit}. The optimal tuning of these parameters was done using the development database. Receiver Operating Characteristics (ROC) representing True Positive Rate (TPR) versus False Positive Rate (FPR) was used to optimize these parameters. A sampling frequency of 1 kHz and threshold value of $f_{crit} = 67\,Hz$ and a Symlet mother wavelet provided maximal discrimination performance.

3 RESULTS

In order to show the performance of the proposed approach, we compared it to classical methods based on the mean (PSD_{mean}) and median (PSD_{median}) frequency of Welch's power spectral density estimation. The following parameters were chosen: order of FFT 256, Hanning window and a data overlapping of 50%. The order of the FFT was chosen to obtain a spectral estimator with low variance while providing a sufficient frequency resolution. The performance of these 3 methods was evaluated on the validation database consisting of 51 recordings of healthy and weak PFM subjects each. Results of Table 1 show that our method outperforms the classical methods in terms of classification error.

Table 2: Discrimination results and estimated central frequency of the compared methods.

	f_o [Hz] (mean±std)		*Classification Error [%]*
	Healthy	*Weak PFM*	
PSD_{mean}	*85±10*	*65±7*	*9%*
PSD_{median}	*72±10*	*52±6*	*7%*
DWT	*77±8*	*53±7*	*4%*

Our method has a lower rate of false discrimination (4%) compared to the two classical methods based on mean (9%) and median (7%) frequency estimation from the power spectral density. The analysis of the estimated frequency f_o used for classification underlines the superiority of the proposed method. For both, healthy and weak PFM subjects, PSD_{mean} gave the highest values of the estimated central frequency while PSD_{median} provided the lowest values. As a good compromise, the proposed method provided values in between these lower and upper bounds. The standard deviations of all three methods were approximately equal. The superiority of our method is related to the fact that the gap in mean f_o between healthy and weak PFM subjects is larger, which provides a better class separation. This improvement in terms of class separation or clustering is also confirmed by the analysis of the histograms of Figure 3. Indeed, the estimator based on the mean frequency of the PSD shows very large and flat clusters with large overlapping. In contrast, our method shows sharper clusters with a larger gap between the maxima of the healthy and weak PFM clusters. Our method had also the lowest cluster overlap which provided in turn best classification performance.

4 DISCUSSION

Our method outperforms classical methods based on mean and median frequency estimation from PSD. The main reason for this improvement may be related to a feature processing in specific frequency bands using a wavelet approach. Information from fast-twitched and slow-twitched fibers contained in EMG-signals is thus projected on different bands. Since urinary continence requires strong and fast muscle contraction (Shishido et al., 2008) and therefore increased recruitment of the fast-twitched fibers, the proposed method is ideally suited to gather this information in the HF-bands (over 60 Hz).

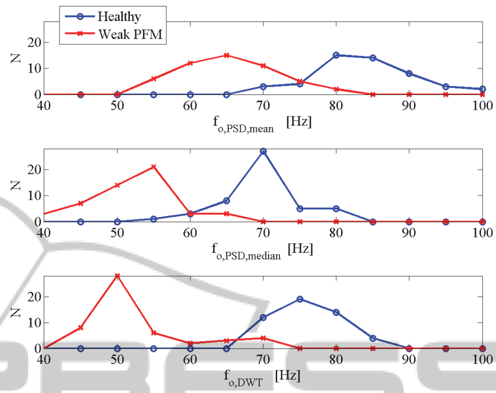

Figure 3: Histogram of estimated central frequency based on the mean and median frequency of the PSD (top and middle) and proposed method (bottom).

The wavelet based approach allows a simultaneous design of the filter-bank in the time-frequency domain. On one hand, the mother wavelet can be chosen to obtain highest resemblance with the EMG-burst activity. On the other hand, the choice of a dyadic base for the scaling and an appropriate sampling frequency provides the optimal location of the frequency bands.

The dyadic filter bank characteristics of the proposed approach could also have been approached in the PSD domain though an appropriate choice of the FFT order in Welch's method and subsequent band grouping. Whether FFT band grouping or wavelet filter bank is to be preferred depends mainly on application specific implementation requirements (Tscharner et al., 2003).

Interestingly, we exploit only indirectly the scale specific signal variance in order to describe dynamic characteristics in terms of the estimated central frequency. Throughout the development phase numerous tests have been performed without success to include additionally scale specific variances using for example neural networks or fuzzy logic. The fact that additional inclusion of scale specific variances in the discrimination approach failed to improve performance could be related to the used vaginal probe, which has lesser sensitivity than more uncomfortable ones (Bø and Sherburn, 2005).

A normalization of MVC scale specific variance versus baseline-scale variances could also have brought along some improvements. Such normalization would have bought the feature to a subject-specific level, which is an important step in a discrimination method (Vaseghi, 2008).

A limitation of the present validation consists in the use of the the Oxford scale as validation criteria for a correct discrimination. The Oxford scale describes a subject's ability to contact maximally the PFM and was assed once. Each subject conducted 4 MVC protocols on 2 different days. Since the outcome of each protocol has not been rated separately, unsuccessful completion of the protocols for healthy subjects may have occurred. The histogram of the central frequency estimated by the proposed approach (see Figure 3) shows that healthy subjects have a very compact cluster. In contrast, weak PFM subjects have a histogram with a long tail into the high frequency domain (> 60Hz). Discrimination errors are due to a misclassification of weak PFM subjects from this marginal tail of the histogram as healthy subjects. Thus, the limitation related to the Oxford scale should not have an influence on the performance of the proposed algorithm presented herein.

5 CONCLUSIONS

Wavelet decomposition together with AR-modeling provides a method for discrimination between healthy and post-partum subjects with weak PFM capabilities that outperforms classical FFT-based methods.

REFERENCES

Akay, M., 1995. Wavelets in biomedical engineering. *Annals of Biomedical Engineering,* pp. 531-542.

Auchincloss, C. C. & McLean, L., 2009. The reliability of surface EMG recorded from the plevic floor muscles. *Journal of Neuroscience Methods,* pp. 85-96.

Beck, T. et al., 2007. Does the frequency content of the surface mechanomyographic signal reflect motor unit firing rates? A brief review. *J Electromyogr Kinesiol.,* pp. 1-13.

Bø, K. & Finckenhagen, H., 2001. Vaginal palpation of pelvic floor muscle strength: inter-test reproducibility and comparison between palpation and vaginal squeeze. *Acta Obstet Gynecol Scand.,* pp. 883-887.

Bø, K. & Sherburn, M., 2005. Evaluation of female plevic floor muscle function and strength. *PHYS THER.,* pp. 269-282.

Carlo, J., De Luca, L. & Gilmore, D., 2010. Filtering the surface EMG signal: Movement artifact and baseline contamination. *Journal of Biomechanics,* p. 1573–1579.

Croce, R., Miller, K., Chamberlin, J. & Filipovic, D., kein Datum Wavelet analysis of Quadriceps power spectra and amplitude under varying levels of contraction intensity and velocity. *'Accepted Article', doi: 10.1002/mus.24230.*

Guyton, A. C. & Hall, J. E., 2011. *Textbook of Medical Physiology.* Philadelphia: Elsevier.

Hermens, H. J., Freriks, B., Disselhorst-Klug, C. & Rau, G., 2000. Developement of recommendations for SEMG sensors and sensor placement procedures. *J Electromyogr Kinesiol.* , pp. 361-74.

Lauper, M. et al., 2009. Plevic floor stimulation: what are the good virbrations?. *Neurourol Urodyn.,* pp. 405-10.

Shishido, K. et al., 2008. Influence of pelvic floor muscle contraction on the profile of vaginal closure pressure in continent and stress urinary incontinent women. *J. Urol.,* p. 1917–22.

Tscharner, V., 2000. Intensity analysis in time frequency space of surface myoelectric signals by wavelets of specified resolution. *Journal of Electromyography and Kinesiology,* pp. 433-445.

Tscharner, V., Geopfert, B. & Nigg, B., 2003. Changes in EMG signals for the muscle tibialis anterior while running barefoot or with shoes resolved by non-linearly scaled wavelets. *Journal of Biomechanics,* pp. 1169-76.

Vaseghi, S. V., 2008. *Advanced Digital Signal Processing and Noise Reduction.* s.l.:JOHN WILEY & SONS, LTD.

Vetter, R., 1999. *Extraction of Efficient and Characteristic Features of Multidimensional Time Series,* Lausanne: PhD Thesis, Swiss Federal Institute of Technology.Vetter, R. et al., 1998. Subband modeling of the human neuro-cardiovascular system: new insights into cardiovascular regulation. *Ann. Biomed. Eng.,* pp. 293-307.