

WAVELET PACKET ANALYSIS FOR ANGULAR DATA EXTRACTION FROM MUSCLE AFFERENT CUFF ELECTRODE SIGNALS

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Abstract- Rehabilitation devices can greatly benefit from the use of natural sensors. Thus, we have extended on our efforts to extract angular information from muscle afferent nerves by means of cuff electrodes. In this study we applied wavelet analysis to electroneurographic (ENG) data from rabbits. In order to estimate ankle flexion/extension angles, we recorded ENG signals from the left Tibial and Peroneal nerves, both during FES and under passive motion. Several processing methods were used for extraction of angular data and were compared with the wavelet analysis. An artificial neural network (ANN) was used with the analyzed features to improve on the accuracy of the angular predictions. The network has so far been tested for local generalization only. The ANN was found to work better with the wavelet features than with previously explored rectified and bin integrated (RBIN) signals. Best results were obtained by using ANN inputs that consisted of both the output from a single wavelet packet node and the RBIN signal: the mean angle prediction error was 1.2°. Exciting as this result is, we must keep in mind that due to the local generalization scope of this study, angle predictions have yet to be assessed regarding inter-rabbit variability.

Keywords – Natural sensors, neural prosthesis, implanted cuff electrodes, functional electrical stimulation, wavelets, artificial neural networks, nerve signals.

I. INTRODUCTION

Closed-loop FES control can greatly benefit from the use of reliable sensory information pertaining to the output angular trajectories. The angular information can be obtained from sensory nerve fibers that monitor the mechanical state of musculotendinous tissue, namely, the muscle afferent fibers. Thus, our research group has been using implanted cuff electrodes to extract angular information by analyzing electroneurographic (ENG) signals obtained directly from the nerve bundles that carry it. So far [1, 2, 3] rectified and bin integrated (RBIN) ENG signals have been monitored and have been found to allow for a reasonable mapping onto angular data by means of neural and fuzzy techniques. However, in [4] it was shown that the RBIN method is unsuited for signals with very low signal-to-noise ratios, which is often our case. This underlines the need for other ENG features to be explored.

Time-frequency domain features carry crucial ENG information. To predict the instantaneous angle at a joint, the static muscle length information must be separated from the dynamic length changes. The afferent fibers carry frequency coded information pertaining to a muscle's static and dynamic length. The information is carried by the static and dynamic fibers within much the same frequency band. However, at the lower frequencies the static and dynamic signals may be separable from each other. This may be

done, at least in principle, by high resolution time and frequency analysis of the muscle afferent signals. Several techniques are available for time-frequency analysis, including short-time Fourier, Wigner-Ville, and Gabor transforms [5]. Wavelets (both continuous and discrete) can also be used for this purpose, but they have the advantage that they allow greater selectivity within the time-frequency domain than the other methods. Thus, this study presents our findings from wavelet packet analysis applied to extraction of angular information from muscle afferent ENG.

II. METHODOLOGY

A. Experimental Setup

Acute experiments were conducted with 2 female New Zealand rabbits. The rabbits were pre-anesthetized with an injection of Midazolam (2.0 mg/kg; Dormicum™, Alpharma, Norway). Then, after 15 to 20 min, anesthesia was initiated by an injection of Hypnorm™ (0.095 mg/kg Fetanyl + 3.0 mg/kg Fluranison; Janssen Pharmaceutica, Belgium). The anesthesia was maintained by applying intramuscular injections of Dormicum™ (0.15 mg/kg Midazolam), and Hypnorm™ (0.03 mg/kg Fetanyl + 1.0 mg/kg Fluranison) every 20 min. All procedures were previously approved by the Danish Committee for the Ethical Use of Animals in Research. During the experiments the rabbits were placed onto a mechanical device for fixating the knee and ankle joints in place (see [3] for more details).

For extracting the ENG signals, tripolar cuff electrodes were implanted onto the Peroneal and Tibial branches of the sciatic nerve in the left hind limb. The Tibial and Peroneal nerves were transected just above the ankle joint to minimize sensory inputs from the foot. Further, to minimize cutaneous inputs, the sural nerve was transected distal to its origin in the Tibial nerve. The internal diameters for the cuff electrodes were 2 mm for the Tibial nerve and 1.8 mm for the Peroneal nerve. The cuff length was 22 mm in both cases. The cuff electrodes were manufactured according to the procedure described in [6] but, in this case, a longitudinal cut was made to open the cuff.

Arbitrary angular trajectories were generated both with FES and by passively rotating the joint through the extension and flexion ranges. For stimulation purposes, percutaneous stainless steel wires were placed intramuscularly into the Tibialis anterior and lateral gastrocnemius muscles, respectively, in the same hind limb as the cuff electrodes. A constant current stimulator was used with the output set at 5mA, 80Hz.

An optical angular transducer was used for measuring the real joint angles.

B. Signal Processing

The ENG signals were sampled at 10kHz after being submitted to a bandpass analog filter (1st order Butterworth, 500Hz to 2kHz bandpass). To eliminate stimulation artifacts when FES was applied, ENG was recorded only for 8ms before each stimulation pulse [7].

A digital FIR (N=120) filter was designed - using the Hamming window method - and used for filtering the sampled ENG signals with various pass-bands. An optimal filter configuration (among 100 tested) was chosen based on the maximum correlation between the processed ENG and known joint angles. For filter selection, the angles were correlated with the following ENG features:

- RBIN
- threshold-based RBIN (Th-RBIN) [4],
- variance,
- autocorrelation (sum of lag 0 to 2),
- 4th order cumulant (as suggested in [4]),
- maximum eigenvalue, and
- summation of different bands in the power spectrum density domain.

These features (except the last one) were also used later for comparison with the wavelet analysis method.

The Th-RBIN signals were derived from a threshold-based technique [4] that required prior knowledge of the angular data. Thus, it is included here for reference purposes only. However, even though threshold-based methods are known not to be robust if used on time-varying signals, its use here illustrates the potential of a future automatic adaptive technique.

The Peroneal channel is expected to have increased activity during ankle extension, while the opposite is true for the Tibial nerve. Thus, to analyze the correlation of both individual signals with both joint flexion and extension, the angular domain was split into flexion and extension subdomains prior to the analysis. Further, the obtained feature histories were submitted to an FIR smoothing filter (N=20) prior to the analysis as well. This is necessary as the angular data are under 5Hz, while the extracted ENG features may have information at 40 Hz (as a result of the 80Hz stimulation and the artifact removal technique).

B. Wavelet Packet Analysis

A five level, full wavelet packet decomposition was made on each 8ms bin, resulting in a total of 63 nodes (Fig. 1). Two different values were calculated for each node:

- the absolute values of the sum of the coefficients, and
- variance of the coefficients.

To determine whether the summation of two nodes could perform better than a single node, all possible combinations of two nodes were tested (1953 different combinations).

The following wavelets were used in the analysis:

- Haar,
- Daubechies 4 and 8,

- Symlet 4 and 10,
- biorthogonal 2.2,
- reverse biorthogonal 2.4, and
- discrete Meyer.

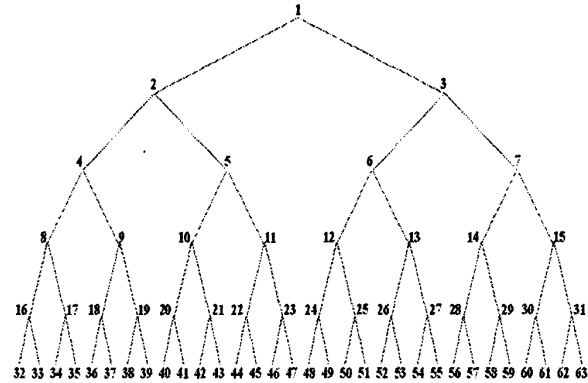


Fig. 1 – Full packet tree for a 5 level decomposition. With the exception of node 1 (preprocessed signal), odd numbered nodes denote the output from highpass filters, while even nodes are outputs from lowpass filters.

B. Artificial Neural Network (ANN)

An ANN was trained to predict the angle from the features provided by the preprocessing and wavelet analysis. The network was composed of a neutral input layer, a 10-neuron hidden layer, and a single output neuron. Tansig transfer functions from -1.0 to 1.0 were used in the hidden and output neurons. To speed up learning, and to accommodate for data range fluctuations, both input and output training and test data were scaled to the (-0.8, 0.8) range. Training was done using the Levenberg-Marquardt algorithm. The amount of training was limited by setting the maximum number of full-set iterations to 1000. On the other hand, the ANN was reinitialized and retrained 5 times for each recording and for each ANN configuration. The best and worst results from this analysis were discarded; the three intermediate trial results were used in the analysis.

The ANN performance was assessed only for local generalization, that is, training and testing were performed with different data subsets, which is always a requirement, but the different subsets belonged to the same rabbits. Thus, no effort has been made yet to evaluate a network that was trained on data from one rabbit but was tested on data from another one (the so called cross-sectional, or global generalization problem).

Based on preliminary tests, the input vector contained either 0, 1, or 2 time delays depending on the ANN used. The signals were split into alternating sequences of length equal to $d+1$, where d is the number of delays. One sequence set was used for network training, while the alternating one was used for network testing. Fig. 2 illustrates the data splitting procedure.

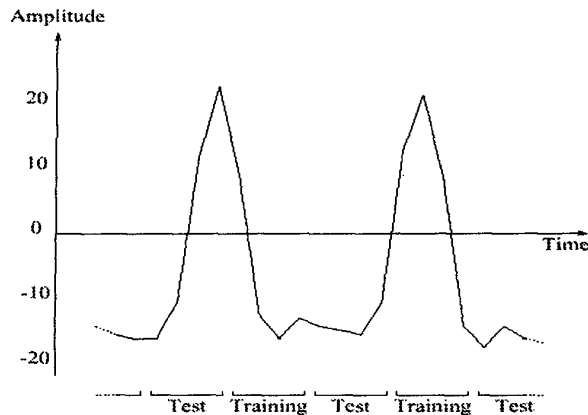


Fig. 2 – Illustrative data split into alternating sets for training and testing, respectively.

Four different network inputs were tested (each with the various delays above):

- the RBIN signal,
- the best node output (determined from the wavelet packet analysis),
- the downsampled applied FES pulse width, and
- the Th-RBIN signal.

Combinations of the above network inputs were also tested.

III. RESULTS AND DISCUSSION

A. Non-Wavelet Features

Table I(a) shows the mean correlation coefficients between several ENG features and the known angular histories. Table I(b) shows which paired comparisons (from Table I(a)) actually yielded significantly different results. From the tables it can be seen that overall the Th-RBIN method is significantly better than the others. It must be recalled that this method required prior knowledge of the real angles, which means that the good results with Th-RBIN may be misleading. Nonetheless, the results do show the potential of the technique if adaptive threshold algorithms are explored in the future. For the Tibial channel, the Th-RBIN algorithm performed significantly than all the other features, while no difference was found among the remaining features (including the RBIN). For the Peroneal channel, the worst performance was obtained with the RBIN algorithm. This poor RBIN performance applies to combined FES-based and passive movements. For the isolated passive movement case, however, the RBIN signals yielded a mean correlation of 0.78 (0.74 for the Tibial channel; 0.82 for the Peroneal channel), not shown on the tables.

TABLE I
CORRELATION RESULTS FOR NON-WAVELET FEATURES.
(a) MEAN CORRELATION VALUES; (b) PAIRED SIGNIFICANT DIFFERENT TEST: YES INDICATES STATISTICALLY SIGNIFICANT DIFFERENCE IN THE MEAN VALUES (WILCOXON TEST, $\alpha=0.05$).

(a)

	Mean	Tibial	Peroneal
RBIN	0.67	0.68	0.66
Th-RBIN	0.76	0.73	0.78
Max. Eigenval. (Max-E)	0.70	0.69	0.71
Var	0.71	0.69	0.72
Autocorr. (AC)	0.71	0.69	0.72
4 th order cumul.	0.71	0.69	0.72

(b)

Tibial	AC	Th-RBIN	MAX-E	RBIN	VAR
Cumul.	no	Yes	no	no	no
VAR	no	Yes	no	no	
RBIN	no	Yes	no		
MAX-E	no	Yes			
Th-RBIN	Yes				

Peroneal	AC	Th-RBIN	MAX-E	RBIN	VAR
Cumul.	no	Yes	no	Yes	Yes
VAR	no	Yes	Yes	Yes	
RBIN	Yes	Yes	Yes		
MAX-E	no	Yes			
Th-RBIN	Yes				

B. Wavelet Packet Analysis

A significant improvement was seen when using wavelet decomposition (as compared to the RBIN method), but only for the Peroneal channel. Both sum and variance operations applied to the Tibial channel ENG decomposition nodes actually led to a worse performance than with RBIN (Fig. 3). The best overall performance was obtained with the rbio2.4 wavelet.

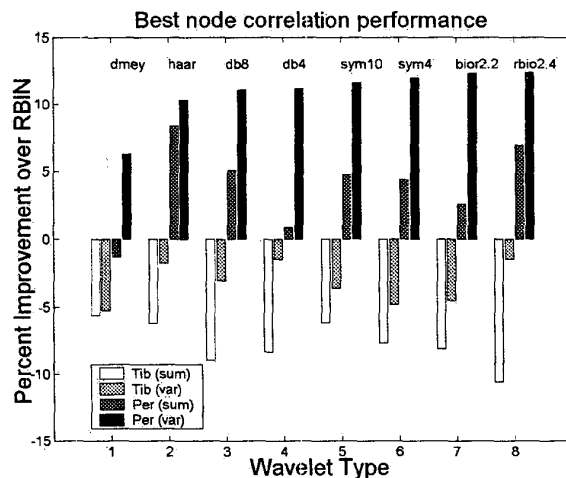


Fig. 3 – Best case scenario: performance of wavelet packet analysis as compared to the RBIN method. The figure includes values only for the wavelet tree nodes that yielded the best correlation with angles.

B. Wavelets Plus ANN

Table II shows the results for several neural network input configurations. Best results were obtained when the ANN had as inputs both the best wavelet tree node output and the RBIN signal (both with one delay associated with each datum). The results for this case are very good: 1.2° mean prediction error and 0.94 correlation between the network's output and the known angles. However, we must remember that these results may apply only to the local generalization situation studied here. Worse results are to be expected in a future global (cross-sectional) generalization study.

TABLE II
MEAN ANN ANGLE PREDICTION PERFORMANCE
(PARENTHESES CONTAIN STANDARD DEVIATION
VALUES). REPORTED VALUES ARE FOR THE TEST SETS.
WN: WAVELET DECOMPOSITION NODE OUTPUT. FESPW:
APPLIED FES PULSE WIDTH.

Network Input	Delays	Mean Error (degrees)	Mean Correlation	% of Errors < 1°
WN	0	2.3 (2.4)	0.81 (0.13)	58.
FESPW	0	2.3 (2.9)	0.79 (0.17)	59.
RBIN	0	2.4 (2.5)	0.73 (0.17)	50.
Th-RBIN	0	2.2 (2.4)	0.78 (0.17)	54.
WN + FESPW	0	1.6 (2.0)	0.88 (0.10)	69.
WN + RBIN	0	1.8 (2.1)	0.87 (0.11)	63.
WN	1	1.9 (2.1)	0.88 (0.10)	62.
WN + FESPW	1	1.9 (2.4)	0.82 (0.18)	69.
WN + RBIN	1	1.2 (1.3)	0.94 (0.05)	72.
WN	3	2.6 (3.3)	0.76 (0.21)	60.
WN+FES	3	3.1 (3.8)	0.70 (0.24)	57.
Th-RBIN + WN + FESPW	0	1.2 (1.6)	0.92 (0.08)	74.

IV. CONCLUSIONS

This study has shown that features from wavelet decomposition can provide better inputs to an ANN than the RBIN method. Further, using the best output from a wavelet packet node in addition to the RBIN signal (plus one input delay per feature) led to a mean prediction error of 1.2°, and a correlation of 0.94 between the predicted and measured angles. However, as exciting as this result seems to be, it may only apply to the local generalization study presented here. Rabbit to rabbit prediction variability is an issue that has yet to be considered in connection with the wavelet and neural network approach.

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REFERENCES

- [1] W. Jensen, R. Riso, and F. Sepulveda 'On-line joint angle estimation based on nerve cuff recordings from muscle afferents'. Proceedings of the 2000 Congress of The International FES Society, Aalborg, Denmark, pp. 376-377, 2000.
- [2] S. Micera, W. Jensen, F. Sepulveda, R. Riso, and T. Sinkjaer 'Neurofuzzy extraction of angular information from muscle afferents for ankle control during standing in paraplegic subjects: an animal model'. *IEEE Trans. Biom. Eng.*, in press, July, 2001.
- [3] W. Jensen, R. Riso, and T. Sinkjaer 'Effect of intertrial delay on whole nerve cuff recordings of muscle afferents in rabbits'. *Neuromodulation*, vol. 3(1) pp. 43-53, 2000.
- [4] B.M. Upshaw, and T. Sinkjaer 'Digital processing algorithms for the detection of afferent nerve activity recorded from cuff electrodes'. *IEEE Trans. Rehab. Eng.*, vol. 6(2), pp. 172-181, 1998.
- [5] S. Qian, and D. Chen 'Joint time-frequency analysis: Methods and applications'. New Jersey: Prentice Hall, pp. 3-47, 1996.
- [6] M. Haugland 'A flexible method for fabrication of nerve cuff electrodes'. Proceedings of the 18th Annual Conference of the IEEE Engineering in Medicine and Biology Society, Amsterdam, pp. 359-360, 1997.
- [7] M. Haugland and A.J. Hoffer 'Artifact-free sensory nerve signals obtained from cuff electrodes during functional electrical stimulation of nearby muscles'. *IEEE Trans. Rehab. Eng.*, vol. 2(1), pp. 37-40, 1994.