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# Wavelet Signal Processing of Human Muscle Electromyography Signals

By

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# Abstract

A novel tool of biosignal processing is proposed to identify human muscle action through sEMG. The tool is based on the integration of continuous wavelet transforms, the Wavelet time entropy and the Wavelet frequency entropy to identify muscle actions through sEMG. The experiments are carried out on triceps, biceps and flexor digitorum superficialis (FDS) muscles. sEMG signals are measured at different intensities of FDS muscle contractions in order to verify the consistency of results. By taking the average entropies and basing it on the lowest average wavelet entropy, it was found in calibrated experiments that the complex Shannon wavelet family is the best candidate to identify the muscle activities among: derivative of Gaussians wavelet family, derivative of complex Gaussians wavelet family, complex Morlet family, Symlets, Coiflets and Daubechies wavelet families. Moreover, the results are consistent with the time-variant signal. The results presented in this paper have futuristic engineering implications in biomedical engineering and bio-robotic applications.

The proposed method has the potential of development, improvement and extension to include other wavelets. Future work includes compromising two wavelets that have different properties on both time and frequency domains, such as the complex Shannon wavelet (with very good frequency resolution but a slow decay in the time domain) and the Meyer wavelet (with good frequency resolution but a faster decay than the complex Shannon wavelet in the time domain), in order to produce optimal results of Wavelet time entropy and Wavelet frequency entropy.

# Preface

This report is a result of my Master's Thesis project conducted at Massey University, Albany Campus.

I wish to express my gratitude to my supervisor Dr Jen-Yuan Chang (James); without his unlimited support and valuable guidance this thesis would not have been possible.

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I hope this report will guide knowledge seekers to further development in the world. I would like to conclude my preface with the following proverb:

*A drop of knowledge is greater than an ocean of strength.*

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# Abbreviations

| | |
|---|---|
| **CWT:** | Continuous Wavelet Transform |
| **DOCG:** | Derivative of Complex Gaussian |
| **DOG:** | Derivative of Gaussian |
| **EMD:** | Empirical Mode Decomposition |
| **EMG:** | Electromyography |
| **FDS:** | Flexor Digitorum Superficial |
| **GT:** | Gabor Transform |
| **HHT:** | Hilbert Huang Transform |
| **IMF:** | Intrinsic Mode Function |
| **sEMG:** | Surface Electromyography |
| **SNR:** | Signal Noise Ratio |
| **STFT:** | Short Time Fourier Transform |
| **TF:** | Time-Frequency |
| **TFA:** | Time-Frequency Analysis |
| **WFE:** | Wavelet Frequency Entropy |
| **WT:** | Wavelet Transform |
| **WTE:** | Wavelet Time Entropy |
| **WFB:** | Wavelet Filter Bank |
| **WVD:** | Wigner-Ville Distribution |

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