A New Method Combining Wavelet Analysis and RBI for Gait Phases Detection in ENG Signals

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Abstract

In this article, a new method that combines a discrete wavelet transform with the RBI method to process cat gait ENG signals is introduced. The method proved to be very efficient in segmentation of the signal into phases, especially in faulty cycles, and can reveal up to five gait phases within a cycle.

1. INTRODUCTION

The possible use of nerve recorded signals in the control of neural prostheses has been introduced by Strange, [2], and Sinkjaer, [7].

Research efforts have now been directed towards extracting gait information from Electroneurographic (ENG) signals in order to design controllers for applications such as active lower-limb prosthesis.

In drop-foot problem correction, Sinkjaer *et al.*, [3] and [4] proposed control methods based on fuzzy and neuro-fuzzy systems, while Strange *et al.*, [1] and [2], implemented a state controller based on thresholding methods. Both approaches relied on tracking occurrence of heel strike and toe off events in the recorded ENG signals.

In this document, the performance of a fifth order discrete wavelet transform and Rectification-Bin Integration (RBI) processing methods for gait phases detection in raw ENG signals are assessed. A new method based on the combination of both techniques previously introduced is then presented, along with associated results and major conclusions.

2. METHODS

2.1. Experiments

Data herein used was recorded on a cat walking on a treadmill. Following anaesthesia, the animal was implanted with a cuff electrode on the left hindlimb peroneal nerve. Following recovery, the animal was solicited to walk on a treadmill. ENG signal was recorded using Victhom's proprietary hardware and software. A sampling frequency of 30 kHz was used, coupled with a band-pass filter (0.1-20 kHz). High-pass filter cut-off frequency value allows eliminating common noise sources and motion artefacts. Low-pass cut-off frequency value is found higher than Nyquist frequency but limited signal frequency content above 2.5kHz allows to mitigate aliasing concerns.

A goniometer (NexGen Ergonomics Model #SG65) was positioned to record the ankle angle variations. The apparatus was set such that the angle equals 0º when it is completely folded on itself and 180º when is completely opened. Typical gait cycle goniometer signal and physiologically relevant events are shown in Figure 1.

A sample of recorded ENG signal and its associated goniometric signal are shown in Figure 2. It is important to note at this point of the work that the ENG signals were scaled by a factor of 10^7 before processing to facilitate visual representation.

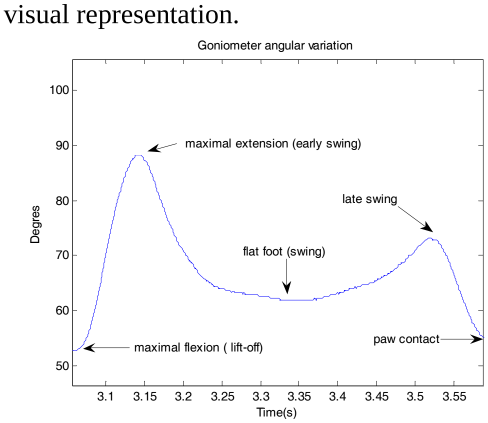

Figure 1: Typical goniometer signal and events

2.2. RBI & Wavelet Comparison

RBI is a commonly used technique, [1], [2], [3] and [6], in ENG signals processing. It is a convenient method for visualizing raw signals segmentation characteristics. A 2.25s portion of the raw signal is rectified and bin integrated with bins length of 5ms. The resulting signal is shown in Figure 3.

The use of wavelet analysis in ENG signals processing was presented by Sepulveda *et al.*, [5]. The authors used a wavelet packet analysed signal to tune a neuro-fuzzy control system and extract joint angular information from the ENG signal. The same raw signal portion used for RBI processing is decomposed with a Coiflet 5 wavelet and the fifth order approximation signal is retained as the denoised ENG signal, Figure 4.

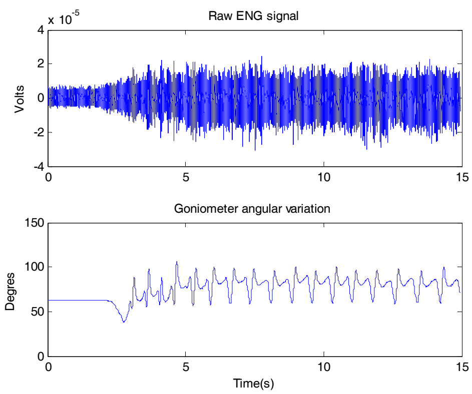

Figure 2: Raw ENG & goniometer signals

The RBI method could not recognize the periodic characteristics of the ENG signal, for some cycles, as shown in Figure 5. For these cycles, identification is not possible unless the goniometric signal is considered. From the footage and goniometer data, it is apparent that these faulty cycles occurred when the cat experienced a poor strike (Figure 4, fourth cycle). However, the wavelet processed signal efficiently identify these cycles, as observed in Figure 6, but shows limited correlation with the goniometer signal.

2.3. The W-RBI method

In order to merge the cycle detection capacity of the wavelet method with the high correlation between the RBI and goniometer data, the RBI of the wavelet transform of the ENG signal (**W-RBI)** was examined. The W-RBI method was capable of both segmenting the different cycles and increasing event detection robustness, Figure 7.

2.4 Multiple Thresholds Technique

In order to sustain fair comparison of the processing methods performance, a simple thresholding algorithm is used based on thresholds selected from the visual analysis of the processed signals, [1].

3. RESULTS

When applying the RBI method to discern different gait phases during faulty cycles, the method fails to discriminate between cycles and phases within each cycle, Figure 5. When considering this signal, the start or end of a cycle can hardly be discriminated without knowing the associated goniometric signal.

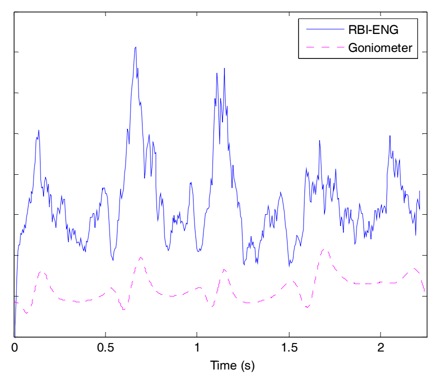

Figure 3: RBI-ENG of four gait cycles

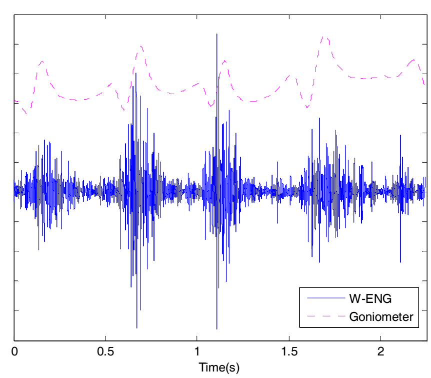

Figure 4: Wavelet denoised ENG signal (W-ENG)

However, features within the wavelet decomposition allowed for greater resolution of the gait cycle events detection. Nevertheless, amplitude-based phase identification still appears unpractical, Figure 6.

Because the wavelet processed signal reveals quite distinctive amplitude variations, the RBI method was applied to the wavelet approximation signal to enhance the discriminative amplitude characteristics. The resulting W-RBI signal is shown in Figure 7. Results allowed both the discriminating of individual cycles in a sequence and distinct phases in a cycle.

Taking advantages of the W-RBI method results characteristics, the multiple threshold technique was successfully applied to detect different phases of a gait cycle in the W-RBI signal. The results are shown in Figure 8 for two different gait cycles.

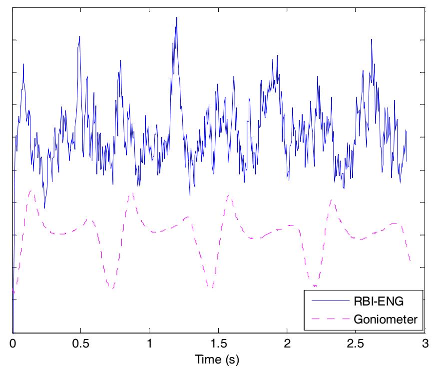

Figure 5: Faulty gait cycles RBI-ENG

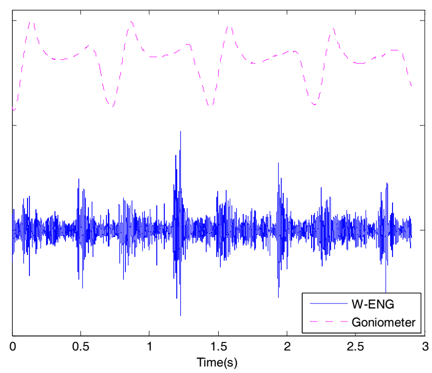

Figure 6: Faulty gait cycles W-ENG

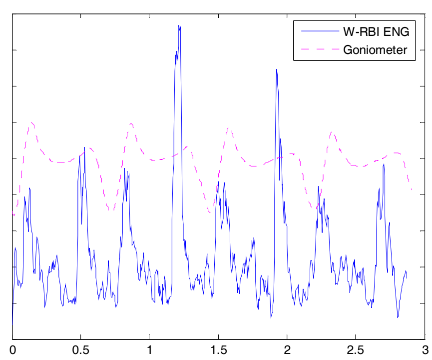

Figure 7: Faulty cycles W-RBI

4. DISCUSSION AND CONCLUSIONS

The multiple thresholds technique applied to the W-RBI signal can identify 5 physiologically relevant phases per gait cycle. This is a result of the W-RBI processing method's capacity to highlight amplitude-based discriminative characteristics. The W-RBI appears to be a simple and efficient method that can be used in ENG signals processing for various applications where controller design rely on amplitude-based segmentation.

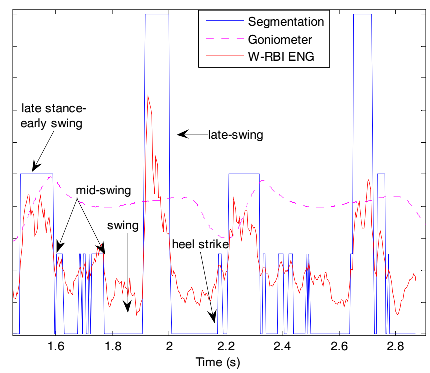

Figure 8: W-RBI signal phase segmentation using multiple thresholds

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