Characterization of Movements during Restless Sleep in Children: A Pilot Study

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***Abstract*— Actigraphy is effective at monitoring circadian rhythms, but often misidentifies periods of restless sleep (defined here as sleep periods with movement) as wake, and periods of quiet wake as sleep. This limitation restricts the effectiveness of actigraphy for investigating sleep disorders. Our objective in this study was to investigate a time-frequency representation of movement during sleep and wake which could ultimately aid in improving classification performance by reducing false wake detections. As a pilot study, we investigate the characteristics of manually labelled movements from six patients (aged 6-12 years, 3 male) during sleep and wake using the over complete discrete wavelet decomposition. The difference between the median wavelet coefficients were analyzed for 30 movement segments from six movement categories during sleep and wake. We found that, in general, the temporal location of high energy coefficients and the energy of the high frequency bands differed between movements during sleep and wake. This indicates that we are able to differentiate movement during sleep and wake with a time-frequency representation. This representation may improve the sleep and wake classification performance by identifying movements specific to sleep and wake. This will likely improve the poor specificity inherent in conventional actigraphy.**

I. Introduction

Actigraphy is a non-invasive tool commonly used to classify sleep and wake for the assessment of sleep disorders. Commercial sleep actigraphy systems typically use a uni-, bi- or tri-axial accelerometer located on the wrist to measure movement, which is quantified as a summarized activity count within a fixed time frame, or epoch (typically 30 seconds). Periods of activity are then classed as wake, and inactivity as sleep [1]. Because of this, actigraphy will often misclassify periods of quiet wake (defined here as wake periods with no movement) as *sleep* and periods of restless sleep (defined here as sleep periods with movement) as *wake* [2]. This limitation reduces the sleep and wake classification performance of actigraphy, particularly when used on patients with disorders where fragmented sleep is a symptom. Developing a methodology for detecting restless sleep may minimize false wake detections and consequently improve the sleep and wake classification performance. There have been some attempts in the literature to identify movement during sleep. One study determined the likelihood of an activity count occurring during sleep based on its surrounding epochs [3]. While this heuristic has been somewhat successful at detecting movement during sleep, it is unclear how effective it would be for patients with fragmented sleep. This is because movement during short periods of wake may be misidentified as having occurred during sleep. Other attempts to detect movements during sleep have used summarized activity counts, focusing on movement duration and frequency [4], [5]. While activity counts are able to detect the occurrence of movement, they are unable to provide the necessary resolution for identifying specific characteristics of movements; for example, the minute limb twitches that occur during rapid eye-movement (REM) sleep [6]. Certain characteristics may allow us to better differentiate movements during sleep from those during wake. However, as conventional analysis is restricted to epoch-by-epoch comparisons of summarized activity, current commercial systems are inadequate. Therefore, there is a need to explore alternatives to epoch-by-epoch activity counts for identifying these characteristics.

Conventional actigraphy in sleep assessment primarily applies time-series methods to derive activity counts within a fixed time frame. However, movement duration and the frequency content of movement can differ over time. This suggests that time-frequency representations may provide movement characteristic quantifications with more sleep and wake discriminatory power than activity counts. Despite this, there have been no known attempts to identify these characteristics. Therefore, the aim of this pilot study was to (1) identify time-frequency characteristics of movement associated with sleep using raw multi-site accelerometry data from a customized accelerometry system, and (2) investigate the utility of these characteristics in discriminating sleep movements from those associated with wake.

II. Method

A. Data Collection

Six patients aged 6-12 years (median 7 years, 3 male) were recruited at the Mater Children's Hospital in Brisbane, Australia. Patients were studied with a full diagnostic polysomnogram (PSG) [7] with simultaneous recording of motion from the left wrist and index fingertip, upper thorax, and left ankle and great toe using a customized continuous multisite accelerometry system (CMAS) [8]. CMAS records 8bit tri-axial accelerometry data (range of $\pm 2g$, where g represents the acceleration due to gravity) at a 100Hz sampling rate. Data were transmitted wirelessly to a receiver unit and logged on a personal computer, separate to the

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PSG system. To aid with post-study data synchronization, the CMAS receiver unit logged ankle and toe data as additional traces on the PSG montage.

B. Pre-processing and movement segmentation

There were a number of preprocessing steps performed in this analysis (refer to Fig. 1 for methodology details and equations). First, the raw accelerometry data were manually synchronized with the PSG recording using custom software. Movement from each child was then manually segmented and labelled into six categories for sleep and wake: body, hand and leg movements each with and without position changes. Hand and leg position changes refer to movements with a final DC offset between the start and end of the accelerometry signal. The corresponding sleep and wake labels were based on the 30s manual scoring from the gold standard PSG. A movement segment was defined as occurring during sleep if the majority of the segment contained REM, or non-REM sleep stages. Similarly, a segment was defined as occurring during wake if the majority of the segment contained the WAKE stage. Five segments of each movement category during sleep and another five during wake were identified for each child, resulting in 30 segments of each category for both sleep and wake.

After movement segmentation, the DC component of the raw data was removed and blocks of missing data of up to two seconds in duration were interpolated using piecewise cubic interpolation. A sliding window was then applied to the labelled segments to determine the start and end of each movement. The start of a movement, a (refer to Fig. 1), was defined as occurring when the total difference between the signal in the current window and the previous window was greater than $0.5g$. The end of a movement, b, was defined similarly; however a sliding window was applied from the end of the segment. Movement was represented using the phase difference between consecutive samples, $\Delta\phi$, and the magnitude of each sample, $|m|$ (illustrated in Fig. 2). The phase difference here represents the angle between the 3-dimensional accelerometry vectors, as defined by the dot product rule (described in Fig. 1). A soft-threshold was applied to the phase difference to account for small oscillations in phase due to noise in the signal [10]. The phase difference between consecutive samples was adopted here in order to avoid undesirable phase wraparound effects ($\pm\pi$), as $\Delta\phi$ is unlikely to pass $\pm\pi$ between adjacent samples. This simple representation of phase also allows us to preliminarily analyze the relevance of phase information without resorting to a complex time-frequency representation.

C. Comparison of movement categories

Movement generally exhibits non-stationary behavior. To fully exploit these characteristics, a representation that summarizes the frequency content over time is desired. Therefore, we used the over complete discrete wavelet transform (OCDWT) to compare the characteristics of the magnitude and phase difference for each movement category during sleep and wake [9]. This algorithm was used to ensure

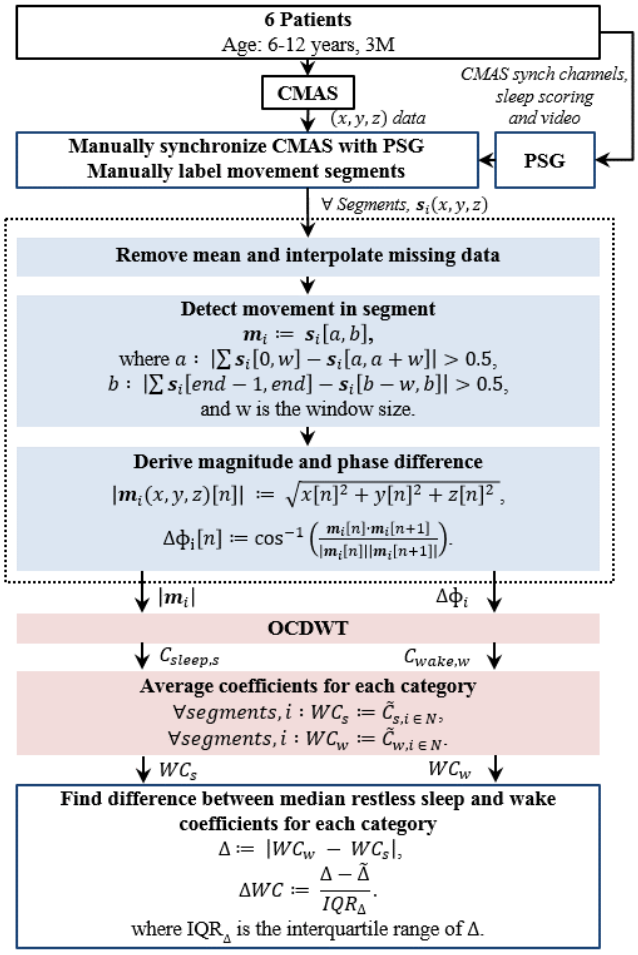

Fig. 1. Methodology for analyzing movement during sleep and wake. Movements were manually labelled from six patients and categorized into *sleep* or *wake* as defined by the polysomnogram (PSG). Movement for each segment was represented by the magnitude ($|m|$) and phase difference ($\Delta\phi$) between consecutive samples. The over complete discrete wavelet transform (OCDWT) [9] was then applied to the representations for each movement. The wavelet coefficients of $|m|$ and $\Delta\phi$ were then averaged for sleep (WC_S) and wake (WC_W) and the difference between these averaged wavelet coefficients (ΔWC) was derived. The difference was then adjusted for the interquartile range (IQR) of all difference values.

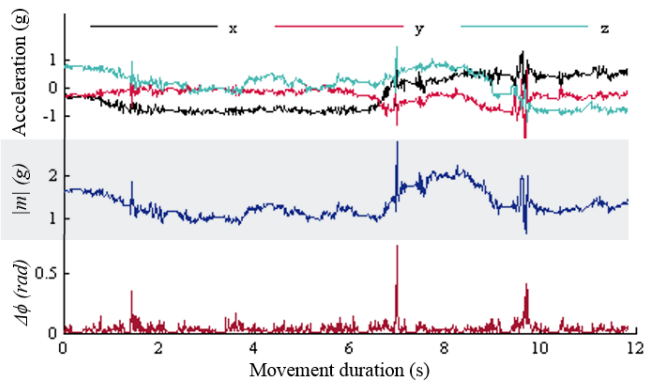

Fig. 2. Example wrist movement with a position change (top) and the corresponding representations. The magnitude of the movement, $|m|$ (center), and the phase difference between consecutive samples, $\Delta\phi$ (bottom), are shown.

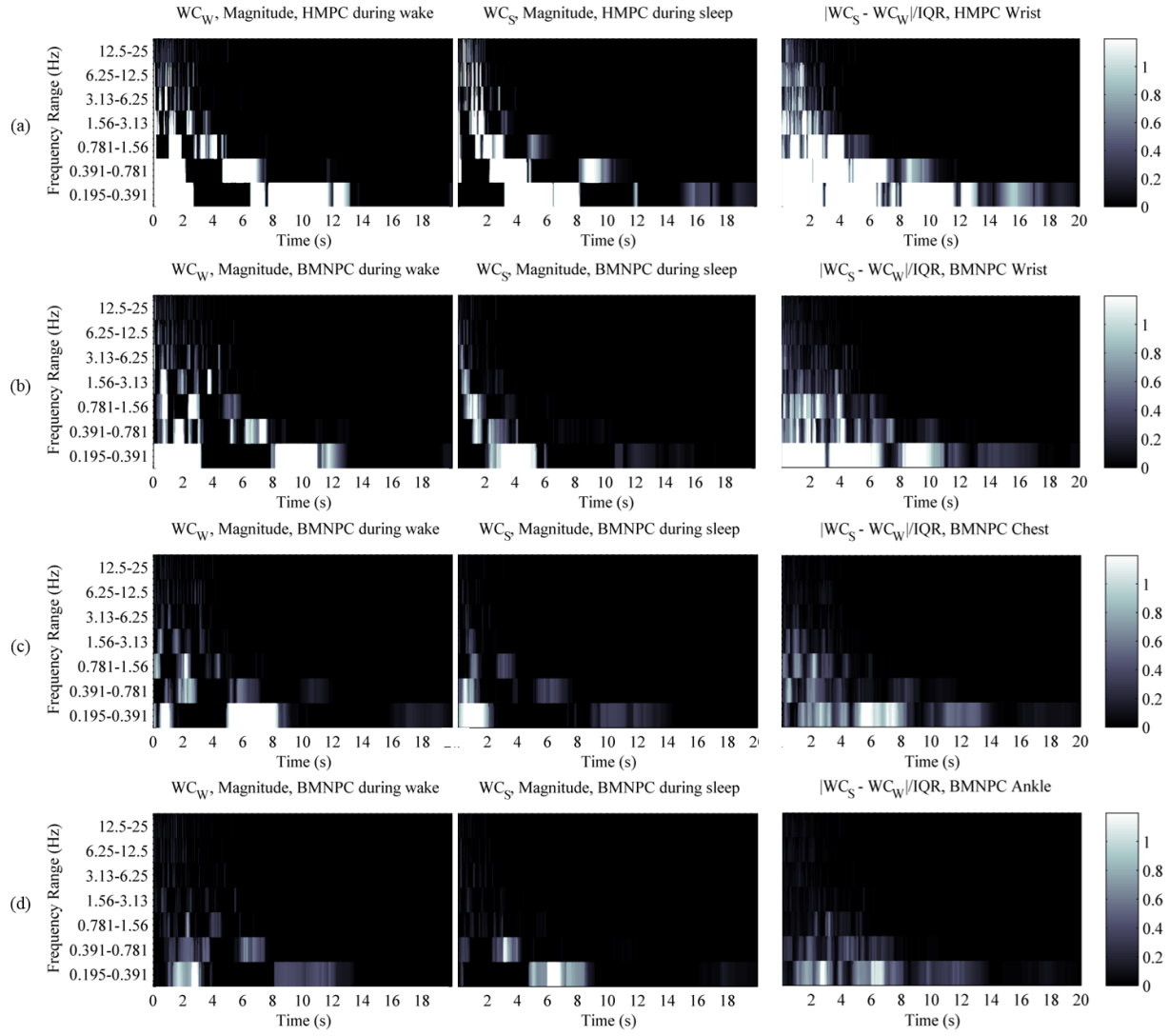

Fig. 3. The frequency content over time for the magnitude of wrist movements with position change (HMPC) (a), and the magnitude of wrist, chest and ankle movements for body movements with no position change (BMNPC) (b)-(d), for six children, showing the median wavelet coefficients and the difference between the median coefficients, adjusted by the inter-quartile range (IQR). The median coefficients for wake (left) and sleep (center), and the difference between the median coefficients during sleep (WC_S) and wake (WC_W), adjusted by the interquartile range (IQR) (right) are shown. The greatest differences in the magnitude for wrist movement in HMPC occurred in the 1.56-3.13Hz band, and the 0.195-0.781Hz bands, (a). The main differences for BMNPC are seen in the 0.195-0.391Hz band for every location, (b)-(d). The wrist showed some additional movement in the 0.391-1.56Hz band, (b). There were no differences in the phase difference for restless sleep and wake.

shift invariance of the signal. Daubechies wavelet function (db5) was used to calculate the wavelet decomposition [13] because of its documented efficacy at representing biosignals [11], [12]. A lower order Daubechies wavelet was used as movement during sleep generally involves temporal bursts of movement with an oscillatory nature. The median of the discrete wavelet coefficients ($C_{S,W}$, refer to Fig. 1) was calculated and notated as $WC_{S,W}$. $WC_{S,W}$ was calculated at each level of the decomposition for the study population within each category during sleep and wake. The difference between the median coefficients (ΔWC), adjusted by the interquartile range (IQR) of all difference values, was then derived for each category. A ΔWC greater than 1 signifies that the difference between the median coefficient for sleep and wake is in the top 25th percentile of difference values. For this reason, we consider a ΔWC greater than 1 to be of interest. This can be likened to a t-test, where values are compared using the difference in means, adjusted by the variance [14]. Here we compare the difference in medians, adjusted by the inter-quartile ranges. The high frequency detail levels, corresponding to 25-100Hz, were removed from analysis as they primarily contain noise.

III. Results

In general, we found considerable differences in hand and body movements between sleep and wake. In particular, there were differences in the 0.781-1.56Hz and 0.195-0.781Hz bands for the magnitude of hand movements with a position change (illustrated in Fig. 3a). There were also differences in the 0.195-0.391Hz band for the wrist, chest and ankle

placements during body movements with no position change (illustrated in Fig. 3b-d), and in the 0.391-1.56Hz bands for wrist movement (illustrated in Fig. 3b). Generally, body movements during wake had greater energy than those during sleep. There were no significant differences in the phase difference between sleep and wake. There were also no obvious differences in leg movements.

IV. Discussion

The objective of this pilot study was to investigate whether movements during sleep can be differentiated from those during wake using time-frequency analysis of raw accelerometry data. There were characteristic differences in the hand movements observed during sleep and wake. Hand movements with a position change had greater energy in the high frequency bands for sleep (shown in Fig. 3a.center). This is likely due to more vigorous movement during sleep; for example, the involuntary twitches of limb extremities that occur during REM sleep [6]. These twitches may contribute to the high energy in the high frequency bands without corresponding low frequency components during sleep. We also found that high frequency movement generally preceded low frequency movement for sleep, whereas the high and low frequency components for wake occurred within the same time frame. This temporal offset may be partly due to the effort of muscle activation caused by atonia [15]. As muscle tone reduces during sleep, muscle activation may require more effort and consequently take longer than muscle activation during wake. Movements during sleep are generally involuntary and hence less controlled than those during wake [15]. This voluntary control of movement is reflected in the low intensity of the high frequency bands for wake. Consequently, hand movements during wake appear to be smoother and shorter in duration to those during sleep. Similar to hand movements, the temporal location of high energy coefficients for body movements differed between sleep and wake. In particular, the low frequency components of body movements during sleep occurred before those during wake. We observed that children would fidget for a period of time before shifting their body while awake, possibly contributing to this temporal offset.

This pilot study has provided some interesting avenues for further research. While our study has demonstrated that there are certain movement characteristics that differ between sleep and wake, increasing both the number of segments from each patient and the number of patients would improve the significance of these findings. The wavelet decompositions indicate that each movement may consist of smaller movements with transitions. For example, the 0.391-0.781Hz band in the body movement decomposition (shown in Fig. 3c.left) is comprised of three segments. It would be interesting to analyze these segments and transitions using a Markov model. In this study, we used the magnitude of each sample and the phase difference between consecutive samples to quantify the raw tri-axial accelerometry signal. While the magnitude was able to represent the signal well, the phase difference appeared to offer little additional information. We observed movement characteristics during sleep that occurred within seconds of similar movement characteristics during wake. However, as the raw accelerometry signal is sampled every 0.01s, the phase difference between consecutive samples is unable to detect these temporal offsets. Applying the complex wavelet transform to capture both magnitude and phase information simultaneously may allow the identification of information which is not apparent when these components are analyzed independently. Future work will investigate whether movement characterizations could improve sleep and wake classification performance.

V. Conclusion

Our results suggest that there are characteristics of movements during sleep that differ from those during wake. In general, our study indicates that movements during sleep and wake can be differentiated by: (1) the temporal location of the high energy coefficients for low frequency bands; and (2) the intensity of the high frequency bands. By classifying sleep and wake based on the characteristics of movements, rather than summarized activity counts, the poor specificity inherent in conventional actigraphy may be improved.

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