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Characterising non-linear dynamics in nocturnal breathing patterns of healthy infants using recurrence quantification analysis

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ABSTRACT

Breathing dynamics vary between infant sleep states, and are likely to exhibit non-linear behaviour. This study applied the non-linear analytical tool recurrence quantification analysis (RQA) to 400 breath interval periods of REM and N-REM sleep, and then using an overlapping moving window. The RQA variables were different between sleep states, with REM radius 150% greater than N-REM radius, and REM laminarity 79% greater than N-REM laminarity. RQA allowed the observation of temporal variations in non-linear breathing dynamics across a night's sleep at 30 s resolution, and provides a basis for quantifying changes in complex breathing dynamics with physiology and pathology.

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1. Introduction

Infant sleep medicine relies on substantial instrumentation in the form of polysomnography (PSG), and manual interpretation of recorded signals to identify and distinguish between physiology and pathology. Such manual interpretation is labour intensive and potentially subjective. As such, there is considerable demand for methods for objectively quantifying recorded PSG signals which provide an insight into the underlying physiology in observational data. Developments in the field of non-linear mathematics have led to speculation that physiological systems, and more specifically human respiratory control, includes non-linear interactions which may be expressed as complexity, non-linear and chaotic dynamics in breathing patterns [1–3]. Consequently, quantifying such dynamics may provide an insight into underlying respiratory physiology, and therefore provide a method for measuring temporal changes associated with pathology or physiological state. Thus in this study, we aim to characterise nocturnal breathing patterns observed in healthy 3 month old infants using the non-linear analytical tool recurrence quantification analysis (RQA).

It has been widely observed that the breathing patterns in infants vary in association with sleep states [4,5] and as such, in the study of nocturnal respiratory physiology, sleep state is an important dynamic consideration. The current criteria for scoring infant sleep is defined by the American Association for Sleep Medicine (AASM) criteria [6], having recently replaced the Anders' criteria [7]. According to this criterion, the overnight PSG is inspected, and states are staged as wake, REM, and N-REM. And indeed, earlier studies have characterised breathing patterns during different sleep states using non-linear measures of complexity such as approximate entropy and correlation dimensions in adults [8,9], and infants [10]. However where these studies analysed relatively long periods of data corresponding to particular sleep state, in clinical practice, sleep states and other physiology of interest are dynamic. Ideally, it would be possible to observe temporal changes in non-linear variables over the course of the night on the basis of 30 s epochs. One mathematical tool which may provide the basis for achieving this is the application of recurrence plot techniques.

The recurrence plot originally proposed by Eckmann et al. [11], is a qualitative tool used to visualise non-linear patterns present in time series data. RQA quantifies structures in the recurrence plot and therefore non-linear dynamics present in the original time series data. Webber and Zbilut [12], and later Marwan et al. [13], proposed a number of different RQA variables which quantify different non-linear features of time-series data. These include: radius (RAD), recurrence (REC), determinism (DET), laminarity (LAM) and entropy (ENT). Unlike many of the traditional non-linear analysis approaches such as correlation dimensions, and Lyapunov exponents, it does not have rigid requirements for data stationarity and long datasets, therefore making it more suitable for application to physiological

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systems. Further, RQA may be applied either to distinct periods of data, or using a moving window approach to allow temporal changes in non-linear dynamics to be observed [14].

Previous research has demonstrated that features derived from RQA of respiratory patterns may be used as sleep state discriminators [15,16] and to automatically classify infant sleep on a 30 s epoch basis [17]. This study expands on this previous work by applying RQA with formal surrogate data analysis to analyse long periods of breathing data from defined sleep states, and using a sliding window methodology to: (a) Confirm that RQA variables are capturing features related to temporal dynamics of breathing patterns rather than simply statistical distribution; (b) Determine whether RQA is able to be used to quantify changes in breathing dynamics associated with temporal changes in physiological state on a 30 s basis; and (c) To characterise the non-linear dynamics of nocturnal breathing patterns using RQA with changes in physiological sleep state.

2. Method

2.1. Subjects and data

Full overnight computerised polysomnography (PSG) (Embla N700) was performed on 25 healthy infants (15 male) aged 3 months $\pm$ 2 weeks who were free of clinically apparent viral respiratory tract infections. PSG included overnight monitoring of electro-encephalogram, electromyogram, electro-oculo-gram, electrocardiogram, oximetry, and respiratory movements measured using Respiratory Inductive Plethysmography (RIP). This data is a subset of a prospective cohort of healthy infants (recruited at birth and followed up over 2 years) [18]. Relevant institutional human research ethics committee approval was obtained (ethics reference: 952C). Each polysomnogram was scored by a trained and experienced sleep technician according to current AASM guidelines [6].

The PSG signal source of interest in this study is abdominal RIP which measures abdominal wall excursions with breathing. The raw data used in this study was sampled at 10 Hz, with 8 bit resolution. This data was further processed to calculate the inter-breath-interval (IBI) series, defined by successive respiratory period, using a tidal amplitude threshold algorithm [19]. In this algorithm, peak inspiratory and peak expiratory points in the RIP data are identified, an amplitude threshold criteria applied, and time between successive peaks calculated. Fig. 1 illustrates typical periods of REM and N-REM breathing as measured using RIP, and the resultant IBI time-series. There is significant literature suggesting IBI is a rich signal source which contains important information about health and disease of the patient or research participant [20–23].

2.2. Recurrence quantification analysis

Recurrence plot analysis is a phase space technique and thus requires data to be embedded in phase space using Takens' time delay embedding theory [24]. Since IBI data is discrete in nature, a time delay of 1 may be chosen, i.e. for a period of time series of IBI data represented by the series I:

$$I = I_1, I_2, \ldots, I_{n-1}, I_n \quad (1)$$

The phase space may be reconstructed for an embedding dimension D

$$\vec{x} = \vec{x}(1), \vec{x}(2), \ldots, \vec{x}(N)$$
$$\vec{x} = [I_1, I_2, \ldots, I_D], \quad [I_2, I_3, \ldots, I_{D+1}], \ldots, [I_{n-D+1}, I_{n-D+2}, \ldots, I_n] \quad (2)$$

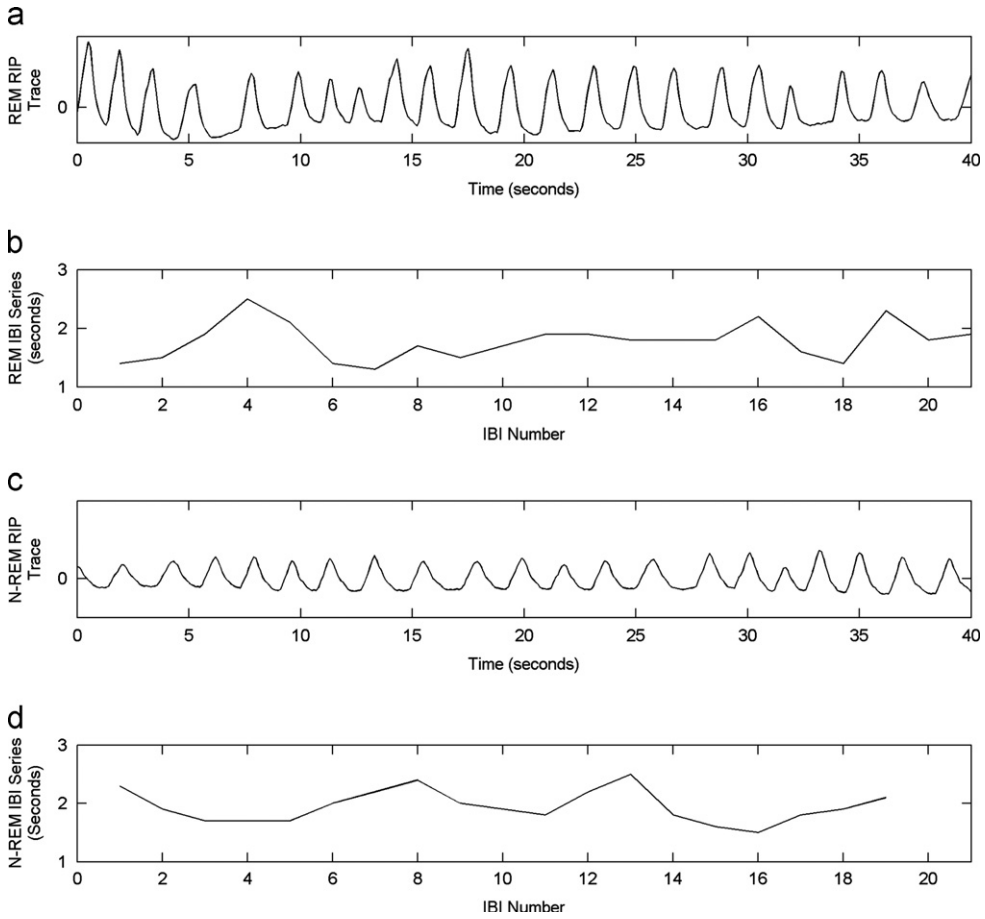

Fig. 1. (a) Sample trace of Respiratory Inductive Plethysmography (RIP) breathing data from an REM sleep period and (b) the derived inter-breath interval series from this REM sleep data. (c) Sample trace of RIP breathing data from a N-REM sleep period and (d) the derived inter-breath interval series from this N-REM sleep data.

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