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Automated artifact elimination of physiological signals using a deep belief network: An application for continuously measured arterial blood pressure waveforms

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ABSTRACT

Artifacts in physiological signals acquired during intensive care have the potential to be recognized as critical pathological events and lead to misdiagnosis or mismanagement. Manual artifact removal necessitates significant labor-time intensity and is subject to inter- and intra-observer variability. Various methods have been proposed to automate the task; however, the methods are yet to be validated, possibly due to the diversity of artifact types. Deep belief networks (DBNs) have been shown to be capable of learning generative and discriminative feature extraction models, hence suitable for classifying signals with multiple features. This study proposed a DBN-based model for artifact elimination in pulse waveform signals, which incorporates pulse segmentation, pressure normalization and decision models using DBN, and applied the model to artifact removal in monitoring arterial blood pressure (ABP). When compared with a widely used ABP artifact removal algorithm (signal abnormality index; SAI), the DBN model exhibited significantly higher classification performance (net prediction of optimal DBN = 95.9%, SAI = 84.7%). In particular, DBN exhibited greater sensitivity than SAI for identifying various types of artifacts (motion = 93.6%, biological = 95.4%, cuff inflation = 89.1%, transducer flushing = 97%). The proposed model could significantly enhance the quality of signal analysis, hence may be beneficial for use in continuous patient monitoring in clinical practice.

1. Introduction

The measurement of physiological signals is crucial for assessing the condition of patients in clinical environments [41]. While the raw values of measured physiological signals can be useful on their own, these signals often carry hidden information that is not readily perceivable without further analysis [38]. However, the physiological signals often contain

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various types of artifacts that can contaminate the information, complicating further analysis [6,22,42]. The detrimental effects from signal artifacts could be particularly problematic during intensive care, where the rapid and accurate diagnosis significantly affects a patient's prognosis.

Arterial blood pressure (ABP) is one of the most important physiological signals acquired during intensive care [7,44], and artifacts could jeopardize the reliability of parameters derived from the monitoring and subsequently lead to unfavorable outcomes [16]. However, previously proposed methods for ABP artifact elimination rely heavily on external physiological signals (i.e., electrocardiogram; ECG) or a predetermined 'morphologic norm' of ABP pulse waveforms (e.g., systolic pressure, diastolic pressure, etc.) [24,37,48] to distinguish the artifact from ABP. The obvious limitation of the former approaches is their dependence on additional physiological signals. The latter approaches also share an important inherent limitation; ABP waveforms can be easily deformed by various artifacts, and it is often difficult to determine whether the deformation is environmental or physiological [25]. Thus, employing predetermined morphological normality to classify artifacts may not necessarily guarantee satisfactory accuracy. Machine learning techniques have recently been highlighted in the field of signal processing due to their success in addressing classic problems of artificial neural network models, such as computational complexity [47]. Nonetheless, the techniques have not been widely applied for the elimination of ABP artifacts.

One technique that exhibits particular strength for processing a vast amount of data with relatively low computational complexity is the deep belief network (DBN), a subtype of the deep learning algorithm. The DBN is a probabilistic, generative learning algorithm that enables the analysis and classification of the distribution of input data using stochastic, hidden layers [49]. By incorporating several simple-structured restricted Boltzmann machines (RBMs), DBN has reduced computational complexity relative to other deep neural networks with complex structures [31]. Although typical shallow models, such as a decision tree or the support vector machine (SVM), may have shorter training times, the DBN is nonetheless advantageous in signal classification because it can describe enormous variations (e.g., increases and decreases in the raw signal), detect regularity from multiple features, and process a substantial amount of signal pulse data with relative ease and because it possesses a strong generalization ability [4,18]. These characteristics of DBN could be suitable for situations in which a high processing speed is required, such as artifact elimination in continuously measured ABP.

This study aimed to introduce a novel method for classifying and automatically eliminating various signal artifacts from continuously acquired ABP pulse waveform signals using the DBN, using only the ABP signals. The proposed method was implemented for the ABP signal. The artifacts in ABP signals can also be generated by both environmental and physiological factors, and the most common types of ABP artifacts are generated by patient movements, cuff inflation, or transducer flushing and biological causes such as blood clots or thrombosis of the arterial line [25,39]. The performance of the DBN for the detection of those common types of artifacts was evaluated.

2. Material and methods

An algorithm using the DBN was constructed to automatically remove artifactual pulses from continuously measured ABP signals. The ABP signal was converted into pulse-wise probabilistic input data for the visible layer of the DBN according to the following sequences: (1) pulse segmentation, (2) labeling procedure, (3) pulse interpolation and (4) normalization. The DBN analyzed the input features and classified the ABP pulses as normal or artifactual. The overview of the process is illustrated in Fig. 1. Initially, the system receives raw signals as continuous time series. Then, the system conducts segmentation of pulse waveforms, labeling, interpolation and normalization to convert the raw data into inputs for DBN. The inputs were then classified as artifactual or normal by the DBN model. Finally, the pulse waveforms regarded as artifacts are eliminated from the raw signal.

2.1. Data acquisition

The ABP signals were acquired from 30 randomly selected patients with traumatic brain injury (TBI) who were admitted to the Neurocritical Care Unit in Addenbrooke's Hospital between 2008 and 2010. The ABP was directly measured through the radial artery (System 8000, S&W Vickers Ltd., Sidcup, UK; and Solar 6000 System, Marquette, USA). Data were sampled over 100 Hz with data acquisition software (ICM+, Cambridge Enterprise, Cambridge, UK, http://www.neurosurg.cam.ac.uk/icmplus). The inclusion criterion was the presence of ABP recordings continuously monitored for a prolonged period from the first day of admission (>20 h) that contained both normal and artifact signals. Informed consent for the retrospective use of collected data for research purposes was obtained from all patients or their relatives, and the relevant research ethics committee approved the study (29 REC 97/291). According to the institutional CPP-/ICP-management protocols for TBI patients [34], all subjects underwent intensive management to avoid systemic hypotension by vasoactive drugs and fluid loading such as norepinephrine (0.5 μg/kg min) and/or dopamine (2–15 μg/kg min).

2.2. Morphological feature extraction from continuous signals

The continuous ABP signals were segmented into pulses, which are the signals from one onset to a consequent onset; the pulse onsets were identified by an automated pulse onset detection algorithm. The initial task for pulse segmentation was to delineate the systolic peaks from the ABP signal. The onset of each pulse was then allocated as troughs that appeared before the systolic peaks. The algorithm for detecting systolic peaks and pulse onsets was developed on the basis of a