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Markov chain modeling and simulation of breathing patterns☆

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ABSTRACT

The lack of large video databases obtained from real patients with respiratory disorders makes the design and optimization of video-based monitoring systems quite critical. The purpose of this study is the development of suitable models and simulators of breathing behaviors and disorders, such as respiratory pauses and apneas, in order to allow efficient design and test of video-based monitoring systems. More precisely, a novel Continuous-Time Markov Chain (CTMC) statistical model of breathing patterns is presented. The Respiratory Rate (RR) pattern, estimated by measured vital signs of hospital-monitored patients, is approximated as a CTMC, whose states and parameters are selected through an appropriate statistical analysis. Then, two simulators, software- and hardware-based, are proposed. After validation of the CTMC model, the proposed simulators are tested with previously developed video-based algorithms for the estimation of the RR and the detection of apnea events. Examples of application to assess the performance of systems for video-based RR estimation and apnea detection are presented. The results, in terms of Kullback–Leibler divergence, show that realistic breathing patterns, including specific respiratory disorders, can be accurately described by the proposed model; moreover, the simulators are able to reproduce practical breathing patterns for video analysis. The presented CTMC statistical model can be strategic to describe realistic breathing patterns and devise simulators useful to develop and test novel and effective video processing-based monitoring systems.

1. Introduction

The Respiratory Rate (RR) is a fundamental vital sign to assess the health condition of a patient: for this reason, it may be important to monitor this parameter continuously in several clinical scenarios. Anomalous trends or values of this parameter can be the sign of a respiratory disease, such as Biot's breathing [1], Kussmaul's breathing [1], Cheyne–Stokes's breathing [2] or Ondine's curse [3], also referred to as Congenital Central Hypoventilation Syndrome (CCHS). More generally, RR abnormal behaviors can be a sign of critical medical conditions. In some cases, they can be an indicator of a potentially deadly event, such as an apnea, which can be defined as a persistent absence of breath or a too low RR. Hence, it is very important to promptly detect these events, which may be occasionally fatal if untreated. Current measurement systems of the RR, also used for apnea detection, are based on polysomnographic devices, which are composed of several sensors. Nevertheless, these systems have some drawbacks: (i) they are expensive and can be used in hospital environments only, (ii) they require specialized staff and (iii) they are moderately invasive due to wired sensors, especially for newborns.

Alternative monitoring systems could yield significant improvements in the welfare of the patients. Hence, non-invasive, low-cost, wireless monitoring and diagnostic systems are under development. Thanks to the recent miniaturization of sensors, wearable health monitoring systems can help to monitor a patient continuously. In [4], modern techniques for the extraction of physiological signals, also related to respiration, are presented. They rely on low-cost technologies and can be a replacement for many sensors used in the clinical environment, despite the fact that they require a "direct connection" to the patient. Contactless RR long-term monitoring, based on the use of ultrasonic sensors for precise distance measurements [5] or the received signal strength in a wireless network [6], were also developed. Among contactless monitoring systems, properly designed video-processing algorithms are of significant interest. In [7–9], contactless monitoring systems are proposed: the first system is embedded in a board with multiple cameras [7], the second one analyzes respiratory movements, but does not include automatic RR estimation [8] and the last one makes

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use of infrared cameras [9]. Some recent innovative video-based systems for RR measurement and apnea detection are based on advanced video-processing algorithms to enhance small breathing motion, improve apnea event detection, and refine RR estimation [10,11].

A difficulty in the design of video processing-based algorithms is the lack of large databases of relevant video recordings properly matched with reliable medical data, due to the rarity of CCHS and severe apnea events, especially in full-term newborns. For this reason, the development of a statistical model of RR patterns, including the occurrence of apnea events, is of significant interest. Such a model can be very useful in order to devise realistic simulators and create a large set of video recordings which allow a more efficient design of automatic RR estimation and apnea detection systems.

In the literature, some physically-based anatomical simulators have been presented. In [12], a hardware system to handle biomechanical movements and simulate an anatomical and functional model of the evolution of the human trunk structures during respiration is proposed. In [13], a system of rigid and deformable parts, which simulates the biological function of respiration for computer animation, is presented.

In this paper, a statistical model, based on a Continuous-Time Markov Chain (CTMC), aimed at simulating the main features of a realistic RR pattern, is derived from medical data. The model parameters are extracted by an inference system for continuous-time Markov random processes. Afterward, the described model is used as background for the definition of two simulators. A *software-based* simulator, able to directly manipulate video recordings of regularly breathing patients in order to introduce artificial breathing disorders, is first presented. A *hardware-based* simulator is also developed: it exploits a manikin equipped with a moving chest to physically reproduce possible breathing disorders according to the proposed statistical model. The developed simulators are then used to test video processing-based algorithms for RR monitoring. This paper expands upon preliminary work appeared in [14], where a two-state model of apnea episodes was proposed.

The rest of the paper is organized as follows. In Section 2, the CTMC-based RR statistical model is presented. Section 3 describes the two developed simulators, software- and hardware-based. Section 4 addresses the validation of the statistical model and the resulting simulators on the basis of previously developed video-based monitoring algorithms. Finally, in Section 5 conclusions are drawn.

2. Respiratory Rate statistical model

The RR is commonly defined as the number of breathing cycles per time unit, typically expressed in breaths per minute [bpm] or, alternatively, in cycles per second [Hz], where a breathing cycle consists of a complete sequence of inhalation and exhalation movements. The RR changes over time, depending on physical activity and health conditions. Normally, the RR of a patient at rest is age-dependent and typically ranges from 30 bpm to 60 bpm (equivalent to 0.5–1.0 Hz) for newborns and from 12 bpm to 20 bpm for adults (equivalent to 0.2–0.333 Hz) [1].

In order to devise a simple model of the RR pattern, it is useful to introduce a finite set of states $\mathcal{S} = \{S_0, S_1, \ldots, S_{N-1}\}$. State S_n, with $n \in \{0, 1, \ldots, N-1\}$, describes breathing with a RR denoted as $\varrho_n \in \mathbb{R}^+$. Occurrence of respiratory pauses or apnea events and large random movements of the patient body are also considered. The statistical model of the RR pattern can encompass all the following conditions.

- If the patient is regularly breathing, i.e. he/she is not suffering from apnea events and no large random body movements appear, the states $\{S_0, S_1, \ldots, S_{N-1}\}$ are used to describe regular RRs, characterized by values $\{\varrho_n\}_{n=0}^{N-1}$ with $\varrho_n \in [R_L, R_H]$, where $R_L > 0$, $R_H > R_L$ denote lowest and highest admissible RRs, respectively.
- If the patient is affected by respiratory pauses/apneas, then the state S_0 is reserved to represent this condition, so that ϱ_0 is formally set to 0 to describe absence of breathing and states $\{S_1, S_2, \ldots, S_{N-1}\}$ are considered for regular breathing.
- If the patient is subject to large random body movements, during which the RR is undetectable, the state S_{N-1} is reserved to represent this condition. The RR ϱ_{N-1} is set to an arbitrary value R_M much larger than the physically acceptable ones: more precisely, ϱ_{N-1} is set to $R_M \gg R_H$. States $\{S_0, S_1, \ldots, S_{N-2}\}$ are still used to represents regular RRs.
- If the patient is both suffering from respiratory pauses/apneas and subject to large random body movements, the states S_0 (with $\varrho_0 = 0$) and S_{N-1} (with $\varrho_{N-1} = R_M \gg R_H$) are reserved for absence of breathing and random movements, respectively. The remaining states $\{S_1, S_2, \ldots, S_{N-2}\}$ are used to describe regular breathing.

The following ordering is assumed: $\varrho_0 < \varrho_1 < \cdots < \varrho_{N-1}$. Since the RR is inherently continuous-valued, each state represents an approximation of the real RR. Therefore, the set $\mathcal{S}$ represents a finite state model of a discrete-valued process approximating the overall RR pattern. The larger the number N of states, the better the approximation at the cost of a higher modeling complexity.

According to the above statistical model, the RR process, denoted as $X(t)$, is defined as a continuous-time process with state space $\mathcal{S}$. The time intervals during which the patient is breathing with rate ϱ_n or is subject to apnea/respiratory pause or large body movements, namely the sojourn times in the corresponding state S_n, can be modeled as random variables and the introduced random process $X(t)$ can be generally described as a Markov process. Ignoring the influence of other vital signs which can modify the RR of a patient over time, such as the heart rate or the oxygen saturation in the blood, the RR pattern cannot be predicted. To derive a model that approximates this stochastic behavior, let us introduce the random variable τ_ℓ, which specifies the ℓ − th sojourn time, where $\ell \in \mathbb{N}^+$ is an index that counts the number of state changes. Jump times can be expressed, in terms of sojourn times, as

$$t_\ell = \sum_{q=1}^{\ell} \tau_q. \tag{1}$$

In Fig. 1, a graphical example of the modeled finite-state RR process $X(t)$ is shown, with highlighted sojourn times and change of state instants.

Since the influence of other vital signs is ignored, it can be assumed that the random variables $\{\tau_\ell\}$ are independent, so that the process $X(t)$ exhibits the memoryless property [15].

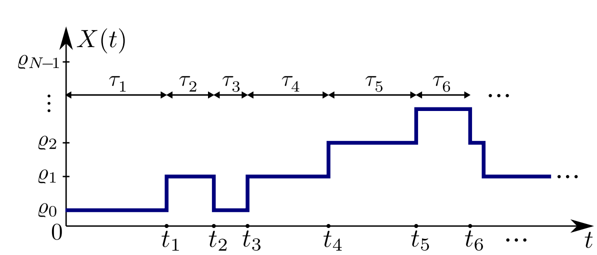

Fig. 1. An example of RR pattern modeled by the finite set $\mathcal{S}$, showing sojourn times and jump times.