Yolo4Apnea: Real-time detection of obstructive sleep apnea

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Abstract

Obstructive sleep apnea is a serious sleep disorder that affects an estimated one billion adults worldwide. It causes breathing to repeatedly stop and start during sleep which over years increases the risk of hypertension, heart disease, stroke, Alzheimer's, and cancer. In this demo, we present **Yolo4Apnea** a deep learning system extending *You Only Look Once* (Yolo) system to detect sleep apnea events from abdominal breathing patterns in real-time enabling immediate awareness and action. Abdominal breathing is measured using a respiratory inductance plethysmography sensor worn around the stomach. The source code is available at https://github.com/simula-vias/Yolo4Apnea

1 Introduction

Obstructive sleep apnea (OSA) is a sleep-related breathing disorder that involves a decrease or complete halt in airflow despite an ongoing effort to breathe [Strollo Jr and Rogers, 1996]. It occurs when the muscles relax during sleep, causing soft tissue in the back of the throat to collapse and block the upper airway. This leads to partial reductions (hypopneas) and complete pauses (apneas) in breathing that last at least 10 seconds during sleep. Most pauses last between 10 and 30 seconds, but some may persist for one minute or longer. We can count from a few tens to several hundred sleep apneas per night. This can lead to abrupt reductions in blood oxygen saturation, with oxygen levels falling as much as 40 percent or more in severe cases. A recent literature-based study [Benjafield *et al.*, 2019], a suggested that an estimated 936 million adults suffer from undiagnosed OSA worldwide. OSA increases risk for cardiac disease [Tadic *et al.*, 2020], stroke [McDermott and Brown, 2020], neurodegenrative diseases such as Alzheimer's [Lajoie *et al.*, 2020], and cancer [Brenner *et al.*, 2019] [Almendros *et al.*, 2020].

Sleep laboratories perform *polysomnography* or a *sleep study* to diagnose sleep disorders. Polysomnography records brain waves, the oxygen level in your blood, heart rate and breathing, as well as eye and leg movements as illustrated in Figure 1. The overnight recordings are *manually analyzed* by a sleep technician and annotated for sleep apnea events. The multi-sensor equipment and the skills needed for maintenance and sleep apnea annotation incur **high operating costs** for sleep laboratories making them economically challenging to operate. Moreover, this is a serious bottleneck in making sleep labs available to a billion people. Hence, there is dire need to automate detection of OSA events and assist a sleep technician achieve high accuracy and throughput.

Deep neural network (DNN) models such as *long short term memory* (LSTM) networks have been tried to automate prediction of OSA events from patterns of expansion and contraction seen in abdominal breathing signals [Van Steenkiste *et al.*, 2018]. The authors achieve an mean true positive rate of only 80% by observing fixed length N (= 30) seconds of abdominal breathing. The poor results can be attributed to the *variable length of an apnea event* and *sleep apnea events spaced at variable distances*. There is a need for a *dynamic approach* to automatically detect variable OSA events and perhaps go a step forward and do so in real-time such that immediate action can be taken.

Yolo4Apnea is real-time apnea detection system based on training *You Only Look Once* YOLO [Redmon *et al.*, 2016], a DNN architecture capable of real-time object detection. Yolo4Apnea can predict OSA events of variable size from 2D images of the time series of abdominal breathing achieving a frame rate upwards of 30 fps with varying levels of confidence. The confidence in percent helps a sleep technician certify automatically predicted OSA event annotations.

The rest of the paper is organized as follows. In Section 2, we briefly present the Sleep Heart Health Study used to train Yolo4Apnea. In Section 3, we present the architecture, evaluation, and target users of Yolo4Apnea.

2 Sleep Heart Health Study Dataset

The Sleep Heart Health Study (SHHS)[1] is a multi-center cohort study implemented by the National Heart Lung & Blood Institute to determine the cardiovascular and other consequences of sleep-disordered breathing. The study entailed performing *polysomnography* on patients (illustrated in Figure 1) to obtain EEG, EOG, EMG, thoracic (THOR), abdominal (ABDO) respiration, air flow, oximetry, ECG, HR, body

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[1]https://sleepdata.org/datasets/shhs

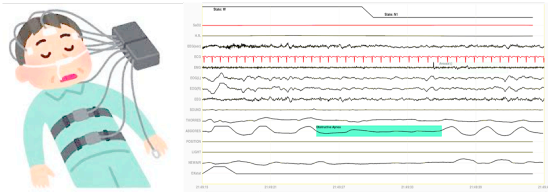

Figure 1: Polysomnography to Detect Obstructive Sleep Apnea

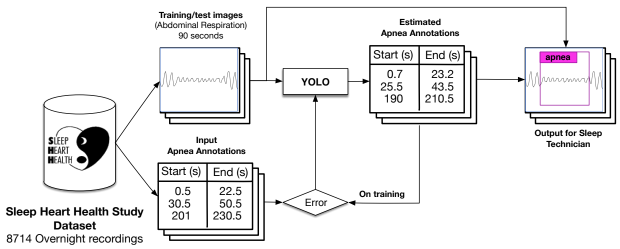

Figure 2: Yolo4Apnea Architecture

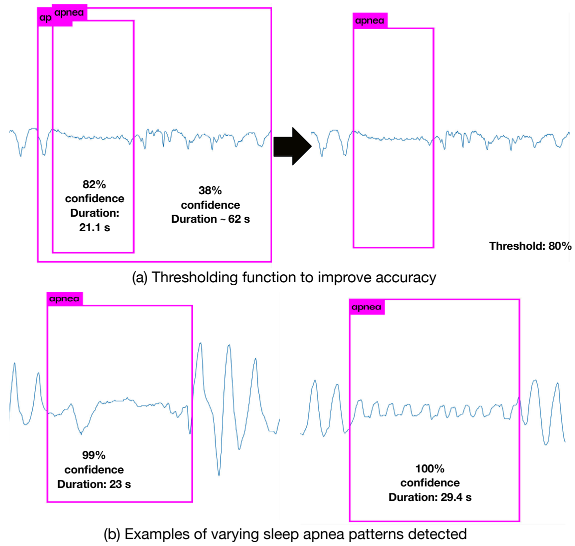

Figure 3: (a) Thresholding in Yolo4Apnea (b) Different sleep apnea patterns

position, and ambient light (ON/OFF) all measured while patients sleep overnight. In all, 6,441 men and women aged 40 years and older were enrolled between 1995 and 1998 to take part in SHHS Visit 1. A second polysomnogram (SHHS-2) was obtained in 3295 of the participants between 2001 and 2003. SHHS study provides annotated OSA events primarily on abdominal respiration data.

3 Architecture

Yolo4Apnea relies on YOLO, a real-time object detection system [Redmon *et al.*, 2016]. YOLO is a fully convolutional neural network (FCNN) that passes an image once through the FCNN and generates an output bounding box around one or more objects found in the image. YOLO is trained by optimizing sum squared error between predicted bounding box and a hand annotated bounding box around an object of interest. YOLO is specifically implemented using Darknet[2] which is an open source neural network framework written in C and CUDA. It is fast and can process up to 45 frames per second on a Titan X GPU [3] allowing for real-time object detection in a video stream.

Yolo4Apnea leverages the ability to generate bounding boxes around OSA events in 2D images of abdominal breathing. It is based on training YOLO's FCNN architecture using 2D images of times series data containing abdominal breathing patterns as shown in Figure 2. The images are created by converting abdominal breathing signals from SHHS (available in the EDF format [Kemp and Olivan, 2003]) into 2D plots normalized between -1 and +1 on the Y-axis and deciseconds on the X-axis. In the full SHHS dataset, the median duration of an OSA event was about 22.8 seconds. Very rarely were OSA events longer than 90 seconds. Therefore, each training image containing an OSA event was scaled to accommodate a 90 second long breathing sequence. The *start* and *end* times of OSA events in the SHHS dataset (available in XML annotation files) is used to automatically create a bounding box to train YOLO as shown in Figure 2. Several thousand training images and bounding boxes were generated from the SHHS data to train YOLO. During training the difference between predicted start and end time (bounding box) and ground truth bounding boxes is used to improve the FCNN's performance.

3.1 Evaluation

Yolo4Apnea predicts an apnea with different confidence levels. In Figure 3 (a), we illustrate how thresholding of confidence level generates multiple bounding boxes. By increasing the threshold to a minimum of 80% confidence, we are able to accurately predict OSA events. Yolo4Apnea is able to automatically predict atypical OSA events as seen in Figure 3 (b). These atypical patterns may arise due to laboured breathing.

3.2 Target Users

General practitioners (GP): Patients with apnea often complain of fatigue and loss in productivity. A simple method for apnea detection can assist GPs screen for apnea quickly. The GP can then recommend a patient to a more advanced analysis at a sleep lab.
Patients at home: The real-time detection of OSA events can trigger actions that stimulate breathing while sleeping. For instance, the automatic diffusion of essential oils [Otaghi *et al.*, 2017] in the air can stimulate breathing or automatically moving the head using a smart pillow [4] can relieve restricted breathing.

[2]https://pjreddie.com/darknet/

[3]https://www.nvidia.com/en-us/geforce/products/10series/titan-x-pascal/

[4]https://www.smartnora.com/

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Demo

Material Requirements

- Flow[5] sensors arranged by author (one or two)
- Laptop computer with Bluetooth Low Energy with Google Chrome Browser arranged by author
- Internet access to download Github repo https://github.com/simula-vias/Yolo4Apnea
- Large screen 24” minimum with power supply to be obtained from organizer
- Poster stand to explain Yolo4Apnea to be obtained from organizer
- A large table for the screen and laptop.
- Floor space of $7 - 10m^2$ for bike, poster, table, screen, and presenter.
- No noise produced from the demo.

Demo Modes

The demo will have two modes:
Retrospective demo: The audience will be shown how OSA events are predicted on pre-recorded overnight recordings that are used to test Yolo4Apnea.
Real-time demo: The audience will also experience a real-time demo of Yolo4Apnea. An user will be asked to wear the Flow sensor around the abdomen. A web application based on Web-bluetooth will be used to connect to the sensor on the Chrome browser. The user will be able to see the his/her abdominal breathing pattern in real-time. The web interface will also send the breathing signal to Yolo4Apnea and receive the bounding box in real-time. Therefore, the user can stop the flow of air or test laboured breathing to witness the detection of OSA in real-time.

[5] https://www.sweetzpot.com/flow