Mini Project Report

on

Respiration Rate Detection From PPG

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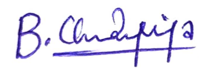
CERTIFICATE

It is certified that the work contained in the project report titled "Title of the Project Report," by "Badiginchala Chandana Priya (Roll No:20bcs026)", "Lalam Divya Sri (Roll No:20bcs072)" and "Ravula Veekshith Reddy (Roll No:20bcs111)" has been carried out under my/our supervision and that this work has not been submitted elsewhere for a degree.

Signature of Supervisor(s)
Name(s)
Department(s)
(Month, Year)

Declaration

We declare that this written submission represents our ideas in our own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in our submission. We understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.



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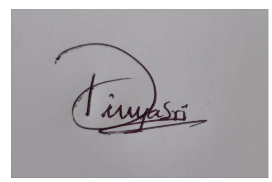

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Approval

This project report entitled Respiration Rate Detection From PPG by Chandana Priya, Divya Sri and Veekshith Reddy is approved for the degree of Bachelor of Technology in Electronics and Communication Engineering.

Supervisor (s)
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Place :

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1 Introduction

The measurement of respiratory rate (RR) in adults, defined as the number of breaths per minute, is a vital indicator of overall health. Typically ranging between 12 and 20 breaths per minute, deviations from this norm can often point to underlying health conditions such as anxiety, acid-base imbalances, hypoxia, and hypercapnia. Recent technological advancements have led to the development of wearable gadgets like smartwatches and rings, equipped with the capability to continuously and remotely capture photoplethysmography (PPG) signals. These signals provide significant insights into breathing patterns, given the profound impact of respiration on the body's blood circulation, leading to observable variations in PPG signals. Consequently, PPG signals have emerged as an invaluable tool for assessing respiratory rate and anticipating the need for medical intervention in various everyday situations. This report delves into the potential applications and implications of using PPG signals for the assessment of respiratory rate and its significance in modern healthcare.

The traditional methods of measuring respiration rate involve a number of complex steps, including the application of many methodologies to extract respiratory data, the analysis of time and frequency, the isolation of components from complex signals, and digital signal processing. These methods are designed for specific patient groups and need regular manual fine-tuning. This entails reconstructing respiratory signals from raw PPG data using a neural network model called a cycle generative adversarial network (CGAN) in order to accurately determine respiratory rates. CGAN is a powerful unsupervised learning tool that can recognize the connections between many data domains and convert input from one domain into the required output from another. This approach simplifies the procedure and does away with the need for manual parameter tuning and tweaking.

The 1-D CGAN is a generative model that is used in machine learning and artificial intelligence. It is intended to generate one-dimensional data, such as time series or sequential data. This model is based on a typical Generative Adversarial Network (GAN) framework, which consists of two basic components: a generator and a discriminator. The generator is in charge of creating synthetic data that replicates the distribution of real data, whilst the discriminator is responsible for distinguishing between real and created data.

2 Related Work

In the realm of estimating respiration rate (RR) from photoplethysmogram (PPG) signals, recent research has made substantial contributions to the advancement of this critical healthcare monitoring technology. This section provides an overview of key findings from a selection of studies, setting the foundation for our proposed approach using Cycle GAN to estimate RR from PPG signals.

Researchers have underlined the importance of RR as a vital health indicator and its potential to serve as an early warning sign for health deterioration, particularly in the context of COVID-19 patients. Reference [1] emphasizes the significance of accurate and continuous RR monitoring, a practice often confined to intensive care units (ICUs). Although PPG signals show promise in RR estimation, as evidenced in subsequent references, their widespread adoption remains a challenge. Shifting our focus to machine learning and deep learning techniques for RR estimation, we encounter ConvMixer, a lightweight deep neural network referenced in [2, 4], as a promising candidate. ConvMixer outperforms other deep learning models, exhibiting low root mean squared error (RMSE) and mean absolute error (MAE) in RR estimation. This underscores the potential of employing deep learning for accurate and efficient RR estimation from PPG signals.

Ensuring the robustness of RR estimation across diverse datasets is crucial for its reliability in real-world healthcare applications. Reference [3] explores the adaptability and performance of RR estimation models across various datasets, emphasizing the importance of inter-dataset generalization in healthcare monitoring.In Reference [5], ConvMixer's remarkable performance in RR estimation is highlighted, leading to its selection as the primary model for further investigation. This research accentuates ConvMixer's potential for real-time RR monitoring, aligning with the increasing demand for continuous, non-invasive health monitoring, particularly in intensive care and remote patient care scenarios.

3 Methodology

3.1 DATASET

The BIDMC dataset is taken from the MIMIC-II resource which is made up of simultaneous IP respiratory signals and PPG recordings from 53 adult intensive care patients that were both recorded for approximately 8 minutes at a sampling rate of 125 Hz. Each record's IP waveform served as the reference respiratory ground truth. Two research assistants independently annotated each breath cycle in the IP signals by hand.

3.2 DATA PREPARATION

The initial stage of the RR (Respiratory Rate) estimation pipeline involves data preparation to ensure the raw PPG (Photoplethysmogram) signals and the respiratory signals are in a suitable format for further processing. The key steps in this stage are as follows:

3.2.1 Normalization

The raw PPG data are first normalized to the range [0, 1]. This step ensures that all PPG signals have a consistent amplitude range, which is essential for downstream processing.

3.2.2 Downsampling

PPG signals are typically sampled at a much higher frequency than necessary for respiratory rate estimation. Downsampling is performed to reduce the data's memory footprint and computational complexity. The original high-frequency PPG signals are downsampled to a common 30 Hz sampling rate while preserving signal integrity.

3.2.3 Window Extraction

To enable effective processing, 30-second windows of data are extracted from the signals. These windows will be utilized in the subsequent stages for the translation from PPG signals to respiratory signals.

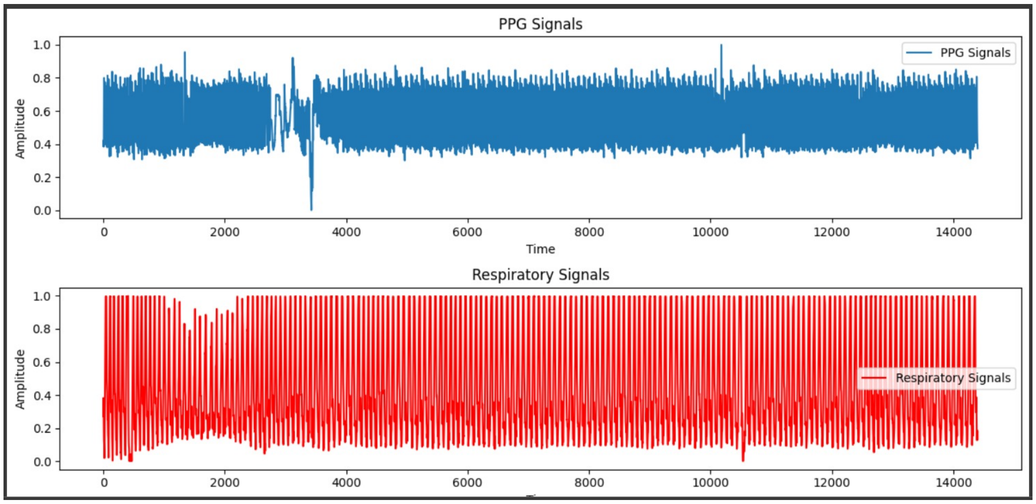

Figure 1. Orginal ppg signals and respiratory signals

3.3 PPG to Respiration Translator(PRT)

In this module, a Cycle Generative Adversarial Network (Cycle GAN) is employed to translate PPG signals into respiratory signals and vice versa. This stage is crucial for generating synthetic respiratory signals from PPG data. The Cycle GAN consists of two main components: generators and discriminators. Here's how it works:

3.3.1 Generator Networks

- There are two generators: G (PPG to Respiratory) and F (Respiratory to PPG).
- These generators aim to create mappings between PPG signals (domain X) and respiratory signals (domain Y).
- They generate synthetic signals resembling the expected signals in the target domain (i.e., PPG to respiratory or vice versa).

3.3.2 Discriminator Networks

- There are two discriminators: DX and DY.
- DX discriminates between real and synthetic PPG signals.

- DY distinguishes between real and synthetic respiratory signals.
- The discriminators help in the adversarial training of the generators.

3.3.3 Loss Functions

The loss functions used in the PRT module include:

Mean Absolute Error: This loss function measures the average absolute difference between the generated respiratory signals and the actual respiratory signals i.e, aims to minimize the average absolute difference between them.

Binary Crossentropy Loss: This loss function measures the dissimilarity between synthetic respiratory signals generated by the generator network and real respiratory signals in the dataset.

3.3.4 Training Objectives

The primary objective in this stage is to train the generator networks to minimize a composite loss function that combines the above loss components. The generators aim to generate realistic synthetic respiratory signals from PPG data while adversarial discriminators attempt to classify real and synthetic signals.

3.4 RR Estimator

3.4.1 Cross-Validation

To ensure robust evaluation, a 5-fold cross-validation technique is applied. The BIDMC dataset is split into five folds, ensuring that each subject's data appears in one fold only. The model is trained five times, with four folds used for training and one for testing during each run. The average MAE of these 5 runs is reported as the final performance result.

3.5 DATA PREPROCESSING

We have loaded and preprocessed the patient data, including PPG and respiratory signals, from CSV files in the dataset. The data is down-sampled to a desired sample rate of 30 Hz. Then normalized the signals to a range of [0, 1].Finally reshaped the data into windows of a specified size (30 seconds at 30 Hz) for training. So, the result of the above leads to a shape of (16, 900, 1), and this is for the single patient. Since we have 53 subjects in our dataset the total number of sample frames are 16 x 53. We used GroupKFold to ensure that data from the same patient stays together within folds. Then performed iteration through the folds and split the data into training and testing sets.

4 Results and Discussions

The CycleGAN model that we have implemented is trained for each fold using the traincyclegan function, where we have build generator and discriminator networks. Adam optimizer is used for both the generator and discriminator networks. The generator networks are trained to minimize the mean absolute error (MAE) loss. The discriminator networks are trained to distinguish between real and fake data. After training, we evaluated the CycleGAN model using the evaluate cyclegan function. It calculates the Mean Absolute Error (MAE) between the synthetic and original respiratory signals.

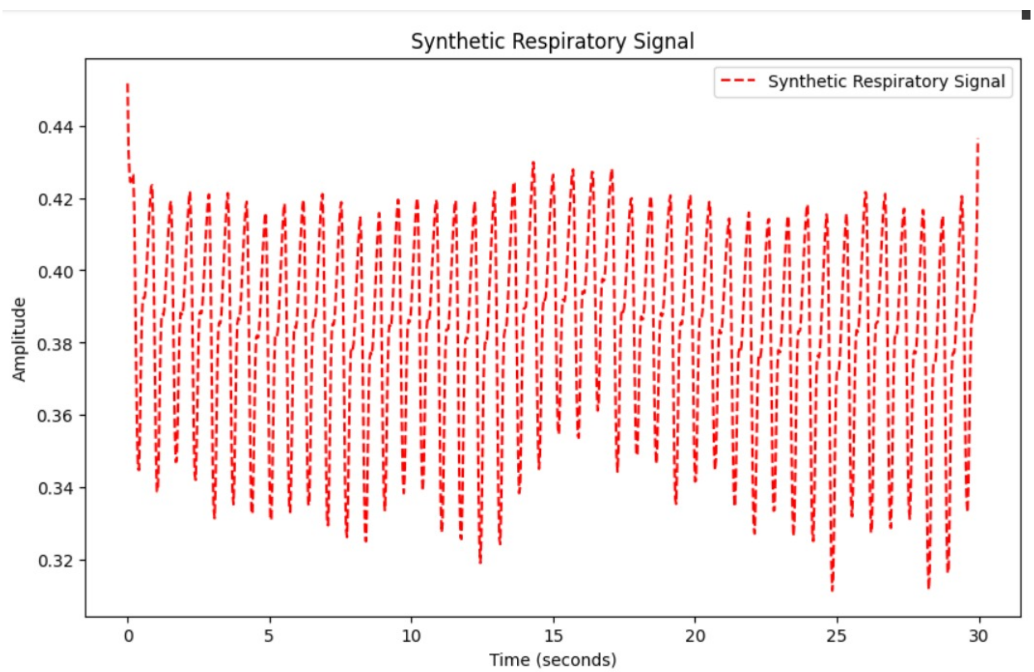

Figure 2. synthetic respiratory signals

- MAE of Fold 1 - 0.26612460945102917.
- MAE of Fold 2 - 0.2108677809769601.
- MAE of Fold 3 - 0.24056590540787892.
- MAE of Fold 4 - 0.22841040709148253.
- MAE of Fold 5 - 0.2687263838432777.
- Average MAE across 5 folds is 0.24393485708596066

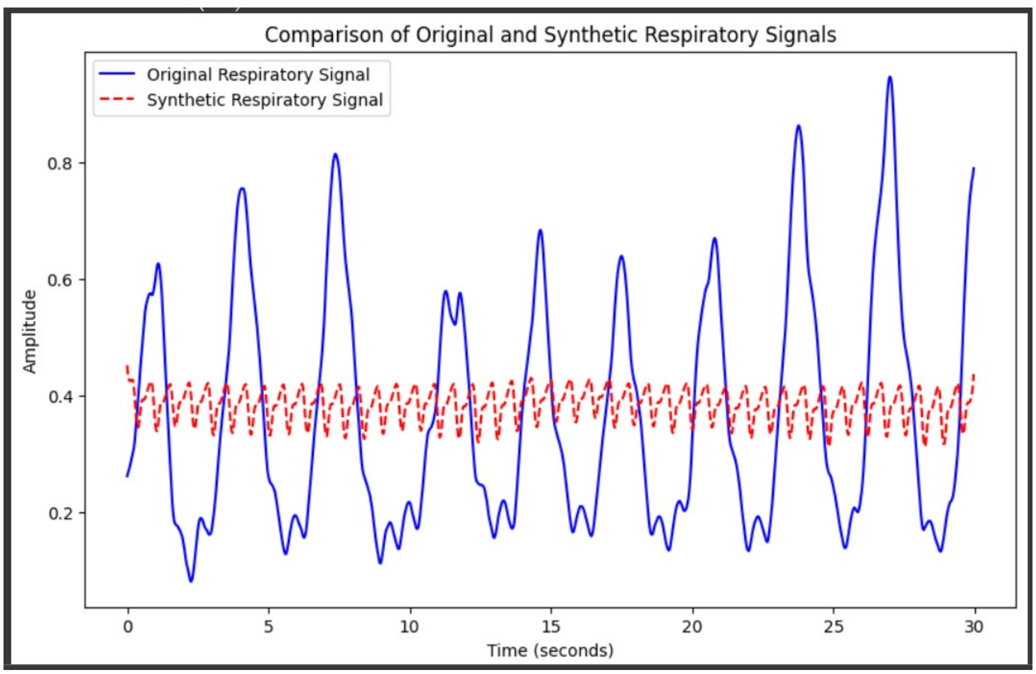

Figure 3. Comparision of generated ppg signals to respiratory signals

5 Conclusion

In the realm of respiratory rate detection through Photoplethysmography (PPG) signals, the utilization of Cycle Generative Adversarial Networks (CGANs) signifies a groundbreaking advancement in healthcare technology. This innovative approach addresses the pressing need for precise and non-invasive methodologies in tracking respiration rates. The CGAN-based methodology eliminates the reliance on manual parameter adjustments and optimizations, a common limitation of conventional respiration rate estimation techniques. This architectural innovation has yielded Respiration Rate (RR) predictions with a remarkable Mean Absolute Error (MAE) of 0.24.

The essence of the CycleGAN lies in its generator-discriminator framework, fortified by adversarial and cycle-consistency losses, which guarantee the precise alignment of PPG and respiratory signals. This synergy of components ensures the accurate mapping between the two domains. Data augmentation techniques, in conjunction with the incorporation of residual blocks, further augment the model's performance and its capability to generalize effectively. This holds particular importance when working with the restricted amount of training data, as it promotes the precision of predictions.

The CycleGAN methodology offers a robust and automated platform for reconstructing respiratory signals, effectively obviating the need for manual fine-tuning and enhancing its adaptability across diverse patient groups. By integrating deep learning and the signal processing techniques, the CycleGAN model becomes adept at discerning intricate patterns and features within the data, ultimately resulting in heightened accuracy and robustness.

The application of CycleGAN in the estimation of respiratory rates holds immense promise for transforming non-invasive health monitoring and elevating healthcare practices to new levels of precision and efficacy.

References

1. Seyed Amir Hossein Aqajari, Rui Cao, Amir Hosein Afandizadeh Zargari, and Amir M. Rahmani. An End-to-End and Accurate PPG-based Respiratory Rate Estimation Approach Using Cycle Generative Adversarial Networks. In 2021 43rd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC). DOI: 10.1109/EMBC46164.2021.9629984.

2. Kapil Singh Rathore; V Sricharan; SP Preejith; Mohanasankar Sivaprakasam. MRNet - A Deep Learning Based Multitasking Model for Respiration Rate Estimation in Practical Settings. In 2022 IEEE 10th International Conference on Serious Games and Applications for Health (SeGAH). DOI: 10.1109/SEGAH54908.2022.9978572

3. Dayi Bian; Pooja Mehta; Nandakumar Selvaraj. Respiratory Rate Estimation using PPG: A Deep Learning Approach. In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine Biology Society (EMBC). DOI: 10.1109/EMBC44109.2020.9176231

4. Lucas C. Lampier, Yves L. Coelho, Eliete M. O. Caldeira, Teodiano F. Bastos-Filho. A Deep Learning Approach to Estimate the Respiratory Rate from Photoplethysmogram. No. 27 (2022): January-June. DOI: https://doi.org/10.17163/ings.n27.2022.09

5. Moajjem Hossain Chowdhury, Md Nazmul Islam Shuzan, Muhammad E. H. Chowdhury, Mamun Bin Ibne Reaz, Sakib Mahmud, Nasser Al Emadi, Mohamed Arselene Ayari, Sawal Hamid Md Ali, Ahmad Ashrif A. Bakar, Syed Mahfuzur Rahman, and Amith Khandakar. Lightweight End-to-End Deep Learning Solution for Estimating the Respiration Rate from Photoplethysmogram Signal. Bioengineering 2022, 9(10), 558. DOI: https://doi.org/10.3390/bioengineering9100558