**Heart Rate Estimation Using Rppg**

Submitted in the partial fulfillment of the requirements for the award of the degree of

# Bachelor of Technology in

Department of Computer Science and Engineering

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**DECLARATION**

The Social Internship Report entitled “**Heart rate estimation using rppg**” is a record of bonafide work of, M. Bellam. Keerthana (2010030017), M. Nissie (2010030095), M. Sravani Chowdary (2010030104), Mounika Reddy (201003485) submitted in partial fulfillment for the award of B.Tech in the Department of Computer Science and Engineering to the K L University, Hyderabad. The results embodied in this report have not been copied from any other Departments/ University/ Institute.

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K L University, Hyderabad is a record of bonafide work carried out under our guidance and supervision.

The results embodied in this report have not been copied from any other departments/ University/Institute

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**ABSTRACT**

With the development of technology, new techniques are rapidly developing for the heart rate measurement process, which is vital, especially in hospitals. Heart rate estimation is of great importance in determining a person's mental and physiological state. In some cases, it is not possible to use many medical devices such as the finger pulse oximeter with PPG technology due to the patient's delicate health conditions. Remote photoplethysmography (rPPG) monitors heart rate without requiring physical contact, which allows for a wide variety of applications. Deep learning-based rPPG has demonstrated superior performance over the traditional approaches in a controlled context. However, the lighting situation in indoor spaces is typically complex, with uneven light distribution and frequent variations in illumination.

Remote monitoring of elderly people or patients in home isolation is an essential part of modern telemedicine. The fundamental idea is based on capturing minute changes in skin color during a cardiac cycle of the human body, involving the inflow and outflow of blood from the heart to other body parts.

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**CHAPTER 1**

**INTRODUCTION**

Telemedicine as a remote clinical service for diagnosis and medical monitoring is a fast-growing public health section. Especially, the COVID-19 pandemic moved it into focus. For all emerging issues in a telehealth session, the face of the patient is an essential source of information about well-being as this is most visible to the health professional. Therefore, it would be beneficial to determine the patient’s condition directly from the face. Heart rate (HR) is a basic parameter of cardiovascular activity. Visual HR estimation, i.e., HR estimation from a video sequence or direct feed from a camera, recently received a lot of attention. Compared to the contact methods, visual HR methods deliver precise readings using cheap measuring devices (such as web cameras). This is particularly important for patients with acute skin conditions. Heart rate is a significant indicator of the functional and psycho-emotional status of humans. Remote photoplethysmography is useful in situations where conventional approaches to heart rate estimation like an electrocardiogram and photoplethysmography require physical contact with the subject is unfeasible. Acquiring the rPPG signal is useful for estimating physiological signals such as heart rate (HR) and heart rate variation (HRV), which are important parameters for remote healthcare. With the development of the computer vision algorithm, remote heart rate measurement using remote photoplethysmography (rPPG) was proposed. Remote photoplethysmography (rPPG) monitors heart rate without physical contact, allowing for many applications. The deep learning rPPG has outperformed traditional approaches in a controlled context.

**CHAPTER 2**

**Literature Survey**

**Literature Survey -01**

**Title: automatic region-based heart rate measurement using remote photoplethysmography.**

This paper was published by IEEE Xplore. The authors are Benjamin, Kossack, eric, anna Hilsman,

Preterist. This paper presents a model-based approach to measuring the vital signs from RGB video files focusing on the heart rate. We use the plane-orthogonal-to-skin (POS) remote photoplethysmography (rPPG) transformation performed individually at five well-defined regions of interest (ROI) in the face. We extract the heart rate information by a correlation of the different rPPGNet signals in these ROIs and a magnitude-based reliability calculation. This increases the robustness of the heart rate extraction from videos. our model-based method is entirely automatic and does not require large amounts of data for training or time-consuming training sessions; our approach can be applied immediately. The ubfc-rppg dataset is used in this research model. our model-based method is entirely automatic and does not require large amounts of data for training or time-consuming training sessions; our approach can be applied immediately

**Literature Survey -02**

**Title: Remote Photoplethysmography signal measurement from facial videos using Spatio-temporal networks.**

This paper is published by the centre for machine vision and signal the analysis university of Oulu. The author is zitong Yu, Xiaobo. In this paper, they estimate heart rate using the techniques like network architecture,3dcnn based phys net, rnn based phys net. MAHNOB-HCL dataset is used. they implemented end to end framework with Spatio-temporal networks which can recover rppg signals from raw facial videos fast and efficiently. Phys net can recover rppg signals with accurate time location of each pulse weak, which allows measuring not only the average hrv level features that enable potential applications in remote a detection and emotion recognition. There was one drawback in implementing these techniques that facial expression analysis for multimode emotional recognition has not been found.

**Literature Survey -03**

**Title: Assessment of deep learning-based heart rate estimation using rppg under different illuminations**

This paper is published by IEEE Xplore. The authors are ze yanghoafei hang, Feng leu.

Remote photoplethysmography (rPPG) monitors heart rate without requiring physical contact, which allows for a wide variety of applications. Deep learning-based rPPG has demonstrated superior performance over the traditional approaches in a controlled context. However, the lighting situation in indoor spaces is typically complex, with uneven light distribution and frequent variations in illumination. It lacks a fair comparison of different methods under different illuminations using the same dataset. In this paper, they present a public dataset, namely the BH-rPPG dataset, which contains data from twelve subjects under three illuminations: low, medium, and high illumination. We also provide the ground truth heart rate measured by an oximeter. We evaluate the performance of three deep learning-based methods to that of four traditional methods using two public datasets: the UBFC-rPPG dataset and the BH-rPPG dataset. The experimental results demonstrate that traditional methods are generally more resistant to fluctuating illuminations. We found that the rPPGNet achieves the lowest MAE among deep learning-based methods under medium illumination, whereas the CHROM achieves 1.5 beats per minute (BPM), outperforming the rPPGNet by 60%. These findings suggest that while developing deep learning-based heart rate estimation algorithms, illumination variation should be taken into account. This work serves as a benchmark for rPPG performance evaluation, and it opens a pathway for future investigation into deep learning-based rPPG under illumination variations.

**Literature Survey -04**

**Title: Multihirerchial conventional network for efficient rppg signal and heart rate from video clips**

This paper is published by the school of information science and technology, northwest university. The authors have panned Zhang, bin li, jin ye Peng, Wei Jiang. UBFC-RPPG AND COFACE datasets are used. The proposed method aims to reconstruct rPPG from RGB facial videos by designing a 3D spatiotemporal convolutional network with multi-hierarchical fusion. the proposed network includes four modules: low-level face feature generation (LFFG), 3D Spatio-temporal stack convolution (STSC), MHFF, and signal predictor (SP). Dataset Our dataset contained a total of 300 VIS videos with a frame rate of 30 fps from 300 objects at the age of 18-26 years. The length of each video was 1 min with a pixel resolution of 1920×1080. These videos were collected by an Honor v30 mobile phone in a well-lit environment. Physiological signals were collected by BIOPAC MP160, including the average HR, respiratory rate, SpO2, ECG signal, and blood volume pulse (BVP) wave of each subject. The physiological signal sampling rate was 1000 Hz. The BF -RPPG database contained 42 videos from 42 subjects. The videos were recorded using a simple low-cost webcam (Logitech C920 HD Pro) at 30 fps with a resolution of 640×480 pixels in an uncompressed 8-bit RGB format. A CMS5OE transmissive pulse oximeter was used to obtain the ground truth PPG waveform and PPG HRs. During the recording, the subject sat in front of the camera with his/her face visible. All experiments were conducted indoors with varying amounts of sunlight and indoor illumination. The OHFA dataset [26] contained 160 videos with high compression rates from 40 subjects (12 women and 28 men); each of the subjects contributed four one-minute videos: two videos in 20 well-lit conditions, and the other two captured under natural light. The videos were recorded using a Logitech HD C525 with a resolution of 640×480 pixels and a frame rate of 20 fps. Each subject wore a contact PPG sensor to obtain the BVP data.

**Literature Survey -05**

**Title: A Deep learning approach for remote heart rate estimation**

This paper was published by agh university of science and technology. the author of this paper was Jaromir Przybyla. The mr-nirp dataset is used. Three data sets, characterized by great diversity, were used to evaluate the proposed algorithm. Two different cameras, eight participants with ages ranging from 22 to 70 years, seven locations with various lighting conditions, and various activities performed by the participants. Ethical review and approval are not applicable for this study, because the article presents a non-contact and non-invasive method of measuring pulse rate. This is only preliminary research and the results have not been used to assess human health. All devices used for collecting the ground truth pulse rate are battery powered and are commercially available products for personal use. Participants were not exposed to any stress - they performed only daily activities, as they did every day. Informed consent was received from all human subjects. The first set of data was recorded using the following configuration. RGB and infrared video sequences were captured using the Intel® RealSense™ camera (model D425). The video acquisition parameters were the following: a resolution of 640 × 480 pixels and a frame rate of 60 FPS. The camera was located 0.5 to 0.6 m from the volunteers. Video duration ranges approx. from 2 to 5 min. Details are provided. Three different locations with various illumination levels were selected. Additional signals were also recorded using a Simple Link sensor Tag CC2650. It is a low-energy Bluetooth device that includes 10 low-power MEMS sensors. The Sensor Tag was placed on the chest of the subject near the neck and face. To measure the ground truth HR and PPG signal, two devices connected via Bluetooth were used. The ECG-based H10 Heart Rate Sensor measured the reference HR. The optical heart rate sensor OH1 captured the PPG signal. Recorded data were used for both: training the LSTM network and testing. The ground truth heart rate (HR) varies from 48 bpm to 128 bpm.

**Literature Survey -06**

**Title: Fusion Method to Estimate Heart Rate from Facial Videos Based on RPPG**

Remote sensing of vital signs has been developed to improve the measurement environment by using a camera without a skin-contact sensor. The camera-based method is based on two concepts, namely color, and motion. The color-based method, remote photoplethysmography (RPPG), measures the color variation of the face generated by the reflectance of blood. In this article, the proposed method is the fusion method for estimation of heart rate using rppg.

First, the face was detected and tracked from the consequence frame of the facial video. Then, photoplethysmography signals were extracted from the face by RPPG. These signals were used to minimize noise and maximize cardiac components. Finally, the heart rate was estimated from the combined signal in the frequency domain. Thus, this study employed the single shot detector] with ResNet trained by the WIDER FACE dataset as mentioned in the article that they conducted several experiments.

This paper mainly focuses to overcome the noise of illumination variance and motion artifacts in RPP

Title: super-high resolution for video-based heart rate estimation with a semi-blind source separation method.

This article states that selecting an appropriate resolution based on a given shooting distance also plays a crucial role to improve the quality of rPPG measurements. Remote photoplethysmography (rPPG), a non-contact technique to estimate heart rates (HR) from video recordings, has attracted much attention from researchers in recent years. It is well-known that rPPG signals can be extracted from low-resolution videos.

**Literature Survey -07**

**Title: Rhythm Net: End-to-End Heart Rate Estimation from Face via Spatial-Temporal Representation**

This article was published by IEEE. The authors of this article are Xuesong Nau,Shiguang Shan, Hu Han. In this paper, they propose an end-to-end Rhythm Net for remote HR estimation from the face. In Rhythmed, they used spatial-temporal representation encoding the HR signals from multiple ROI volumes as to their input. Then the spatial-temporal representations are fed into a convolutional network for HR estimation. they also take into account the relationship of adjacent HR measurements from a video sequence via the Gated Recurrent Unit (GRU) and achieve efficient HR measurement. In addition, they build a large-scale multi-modal HR database (named VIPL-HR 1), which contains 2,378 visible light videos (VIS) and 752 near-infrared (NIR) videos of 107 subjects. The VIPL-HR database contains various variations such as head movements, illumination variations, and acquisition device changes, replicating a less-constrained scenario for HR estimation. The proposed approach outperforms the state-of-the-art methods on both the public-domain and VIPL-HR databases.

**Literature Survey -08**

**Title: Heart Rate Estimation from Facial Videos Using a Spatiotemporal Representation with Convolutional Neural Networks**

This paper is published by IEEE on 30 March 2020. Remote photoplethysmography (rPPG) is a kind of noncontact technique to measure heart rate (HR) from facial videos. As the demand for long-term health monitoring grows, rPPG attracts much attention from researchers. However, the performance of conventional rPPG methods is easily degenerated due to noise interference. Recently, some deep learning-based rPPG methods have been introduced and they revealed good performance against noise. In this article, we propose a new rPPG method with convolutional neural networks (CNNs) to build a mapping between a spatiotemporal HR feature image to its corresponding HR value. The feature map is constructed in a time-delayed way with noise-contaminated pulse signals extracted from existing rPPG methods. The CNN model is trained using transfer learning where images built from synthetic rPPG signals are taken to train the model first in order to generate initials for the practical one. The synthetic rPPG signals are interpolated from blood volume pulses or electrocardiograms through a modified Akima cubic Hermite interpolation. The proposed method is tested in both within-database and cross-database configurations on public databases. The results demonstrate that our method achieves overall the best performance compared to some other typical rPPG methods. The mean absolute error reaches 5.98 beats per minute and the mean error rate percentage is 7.97% in the cross-database testing on the MAHNOB-HCI data set. Besides, some key factors affect the performance of this method.

**Literature Survey -09**

**Title: Remote Heart Rate Measurement from Highly Compressed Facial Videos:**

**An End-to-end Deep Learning Solution with Video Enhancement.**

The authors of this paper are Zitong Yu1, Wei Peng1, Xiaobai Li1, Xiaopeng Hong, and GuoyingZhao. In this paper, the heart rate was estimated by highly compressed facial videos. They proposed an end-to-end deep learning-based propose a two-stage, end-to-end method using hidden rPPG information enhancement and attention networks, which is the first attempt to counter video compression loss and recover rPPG signals from highly compressed videos. The method includes two parts:

1) a Spatio-Temporal Video Enhancement Network (STEVEN) for video enhancement, and

2) an rPPG network (rPPGNet) for rPPG signal recovery. The rPPG Net can work on its own for robust rPPG measurement, and the STVEN network can be added and jointly trained to further boost the performance, especially on highly compressed videos. Comprehensive experiments are performed on two benchmark datasets to show that,

1) the proposed method not only achieves superior performance on compressed videos with high-quality videos pair,

2) it also generalizes well on novel data with only compressed videos available, which implies the promising potential for real-world applications. Two datasets are used – OBF and MAHNOB-HCI.

**Literature Survey -10**

**Title: A deep learning framework for heart rate estimation from facial videos**

This paper was published on 5 December 2020 by Elsevier. The authors are Gee-Sern JisonHsu and ArulMurugan Ambika path. In this paper, their approach is one of the pioneering works that propose a deep learning framework with TFRs as input for solving the heart rate estimation from facial videos. In addition, they have developed a heart rate database, named the Pulse from Face (PFF), and used it along with the existing PURE database to train the CNN. The PFF database is released for research purposes with this paper. They have evaluated the proposed framework on the MAHNOB-HCI database and the VIPL-HR database and compared its performance with that of other contemporary approaches to demonstrate its efficacy. develop a novel deep learning framework for real-time estimation of heart rates by using an RGB camera. This approach consists of the following four steps. We begin Step 1 by detecting the face and facial landmarks in the video to identify the required facial Region of Interest (ROIs). In Step 2, extract the sequence of the mean of the green-channeled video from the facial ROIs, and explore three-stage sequential filtering, including illumination rectification, trend removal, and signal amplification. In Step 3, the Short-Time Fourier Transform (STFT) is employed to convert the 1D filtered signal into the corresponding 2D Time-Frequency Representation (TFR) for characterizing the frequencies over short time intervals. The 2D TFR allows the formulation of the heart rate estimation as a video-based supervised learning problem, which can be solved by exploring a deep Convolutional Neural Network (CNN), as is carried out in Step 4. The approach is one of the pioneering works that propose a deep learning framework with TFRs as input for solving the heart rate estimation from facial videos.

**CHAPTER 3**

**HARDWARE AND SOFTWARE REQUIREMENTS**

**3.1 Hardware requirements**

Hardware requirements for insurance on the internet will be the same for both parties which are as follows:

Processor: Dual Core

RAM: 2 GB

Hard Disk: 320 GB

NIC: For each party

**3.2 Software requirements Operating System:**

Windows10 Ultimate which supports networking.

Python development toolkit.

Command prompt

Python tool kit 3.7.1 and 3.8.0

**CHAPTER 4**

**METHODOLOGY**

In a two-stage end-to-end method, we will first introduce our video enhancement network STVEN. then introduce the rPPG signal recovery network rPPGNet

STEVEN-rPPGNet

Diagram

Description automatically generatedThis deep learning-based method considers low-resolution input video clips to measure the heart rate. Its training occurs in two stages. The first stage involves a video enhancement network (called STVEN) whose output corresponds to spatially enhanced videos. The second stage involves a measurement network (called rPPGNet) whose output provides the heart rate. The measurement network rPPGNet is formed using a spatiotemporal convolutional network, a skin-based attention module, and a partition constraint module. The skin-based attention module selects skin regions. The partition constraint module enables an improved representation of the rPPG signal.

4.1 STEVEN-rPPGNet Implementation.

We planned to carry out our measurements with deep learning methods, which was our main approach. We hoped that deep learning reduced error rates as a result of these measurements. We used the model of the STVEN, which is a video-to-video translation generator aided with fine-grained learning and is the first video compression enhancement network to boost rPPG measurement on highly compressed videos. The rPPGNet, which featured a skin-based attention module and partition constraints, can measure accurately at both HR and HRV levels.

We want to conduct the cross-dataset test and show that the STVEN can generalize well to enhance unseen, highly compressed facial videos for robust rPPG measurement, which implies promising potential in real-world applications

CHAPTER 5

IMPLEMENTATION

5.1 Packages

5.1.1 Matplotlib-

Matplotlib is one of the most popular Python packages used for data visualization. Matplotlib is designed to be as usable as MATLAB, with the ability to use Python, and the advantage of being free and open-source.

5.1.2 Numpy-

NumPy is a very popular Python library for large multi-dimensional array and matrix processing, with the help of a large collection of high-level mathematical functions. It is very useful for fundamental scientific computations in Machine Learning.

**5.1.3- Opencv – python**

OpenCV is a popular Python library for real-time computer vision. OpenCV is a great tool for

image processing and performing computer vision tasks. It is an open-source library that can

be used to perform tasks like heart rate estimation, face detection, objection tracking, landmark

detection.

Text

Description automatically generated

**5.1 Importing Packages**

**5.2 Data pre-processing:**

After reading we found that the UBFC dataset is the best-suited dataset for our project . and after downloading

the dataset Then we have applied feature engineering to the dataset

to clean the data, feature scaling, data pre-processing, and like many more things. Then we had to divide our

dataset into two-part, here the first part consists of the independent feature and dependent feature.

Independent feature, we considered the price, and the independent feature considers the rest of the column.

Then we had to

divide the dataset into two-part, In the first part, we trained the dataset, and in also second part test the

dataset. The data is the most important aspect of a deep learning assignment, to which special attention

should be paid. Indeed, the data will heavily affect the findings depending on where we found them, how

they are presented, if they are consistent, if there is an outlier, and so on. Many questions must be addressed

at this stage to ensure that the learning algorithm is efficient and correct. To obtain, clean, and convert the

data, many sub-steps are required. We will go through these steps to understand how they've been used in

my project and why they're helpful for the machine learning section. Age and floor parameters were handled

for their missing values. the target attribute is also dropped off from the training dataset. Pandas library is

used for this purpose. For statistical visualization of the dataset, the min, max, standard deviation, mean of

the target attribute was found.

**5.3 Model Implementation**

Analyzing data is for extracting accurate estimation from basic information provided. After doing that we

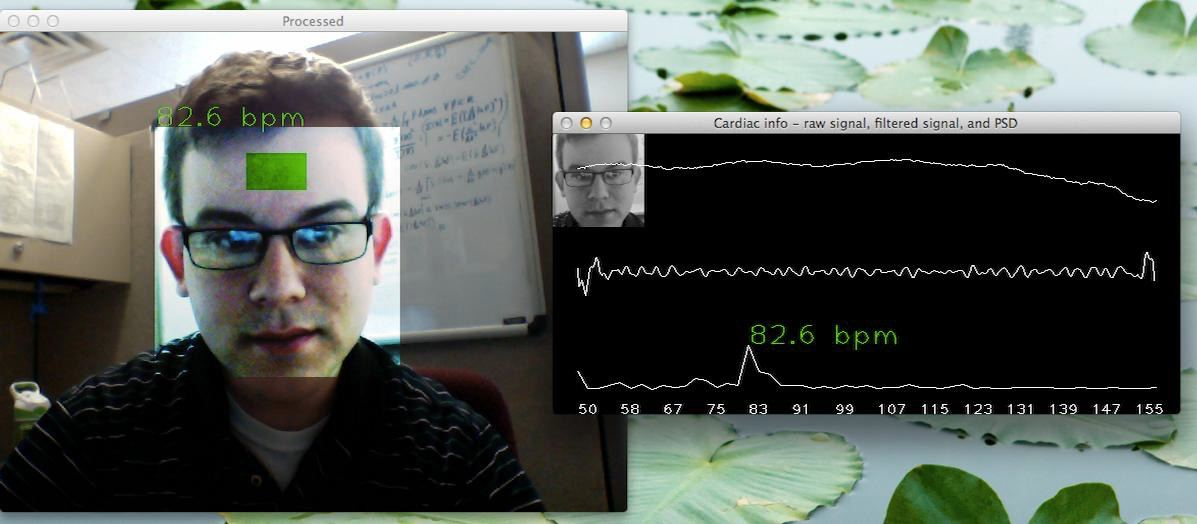
had to train our model with the cleaned dataset. the model selected is stevn-rppg as this has been proven to

be one of the best deep learning models.

**CHAPTER 6**

**RESULTS AND DISCUSSION**

we have applied the de ep learning method to the datasets collected related to our project heart rate estimation After many discussions among our teammates we found that deep learning methods show more accurate results in the prediction of heart rate. This deep learning-based method considers low-resolution input video clips to measure the heart rate.



**6.1 Result**

**CHAPTER 7**

**CONCLUSION AND FUTURE WORK**

Remote heart rate estimation is the measurement of heart rate without any physical contact with the patients. During the pandemic period, telehealth and remote health monitoring have become increasingly important and people widely expect that this will have a permanent effect on healthcare systems.

According to the information from literature studies, we can say that deep learning-based methods generally give more correct and faster results than traditional methods.

**CHAPTER 8**

**Social contribution**

Health care has become pressing and important for people all around the world. Each human being is

conscious of his or her own health. Especially after the global pandemic, we can see a boom in health and

tech. Now a days everyone is trying to make health care like self-assessment, medicine delivery, diagnosis

and online doctor consultancies accessible to common man where they can access it from their home

itself. We think this project plays a part in that. Some people, because of their busy schedules, are unable to

get to a hospital. To assist in this situation, we are developing the heart rate estimation project using rppg.

This project helps individuals check their heart rate contactless. Remote photoplethysmography (rPPG) is

a contactless video-based method that monitors changes in blood volume by capturing changes in the

intensity of skin pixels to measure the pulse.

**CHAPTER 9**

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