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AN ESTIMATION SYSTEM FOR VITAL SIGNS

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Abstract : Now-a-days, as everyone gives priority to their health vital signs estimation system plays a major role in monitoring the health and preventing from diseases. Heart rate (HR) and respiration rate (RR), also referred to as breath rate (BR), are vital indicators that must not be disregarded. Many methods have been proposed to identify these critical indicators. There are two primary categories of methods for measuring HR and BR: contact methods and non-contact approaches. Due to their excellent accuracy, contact methods—as the conventional techniques—are the most commonly used methods for measuring signs.

An electrocardiogram (ECG) or photoplethysmography (PPG) is usually used as the most common method of contact. One of the most commonly used methods for obtaining an ECG signal is to place adhesive gel electrodes on a person's chest or limbs in order to obtain an ECG signal with a significant amount of useful information about vital signs. As an optical technique, PPG is capable of detecting changes in the detected light intensity (i.e., variations in Blood Volume Pulse) in the microvascular bed of tissue. In the meanwhile, the BVP modifications may be used to provide useful information on the circulatory system and estimate BR and HR. Because transmitted light is easily recognized, a PPG sensor is usually placed on the fingertip to effectively monitor fluctuations in blood flow. As a result, PPG has become more well-liked as a contact-based technique in recent years. Nevertheless, because users must typically wear devices that require skin contact, these contact techniques may cause irritation and distress. As such, this endeavor proposes a PPG-based real-time technique for the contactless computation of HR and BR.

***IndexTerms* - Heart rate, Breath rate, Contact less method, Vital signs**

I. INTRODUCTION

Monitoring vital signs has been a hot issue for many scholars in the past few decades. Vital sign monitoring systems benefit humans in many ways, such as patient care and the avoidance of age-related illness in the elderly. Vital signs such as heart rate and breathing rate, also referred to as respiration rate (RR), are becoming more and more important. Measuring vital signs, which include body temperature, respiration rate, heart rate, and oxygen saturation (SpO2), is an essential basic task in biomedical metrology. Conventional equipment often uses contact-based measurement techniques for these kinds of tasks. On the other hand, contact measurement has several shortcomings. Above all, contact between the skin and body increases cutaneous irritation and bacterial contamination. Furthermore, contact-based devices drastically limit the range of motion of patients, which can result in terrible pain. The use of image sensors for contactless vital sign assessment has grown in popularity due to its advantages in terms of patient friendliness and hygiene.

Numerous studies have already been conducted to determine heart rate and oxygen saturation using skin photoplethysmography (PPG), which is assessed using a color camera. In the representative papers, a variety of techniques for heart rate estimate have been published. The core of these techniques is the measurement of the small temporal variation in skin color. Different oxygenated and deoxygenated hemoglobin absorption spectra cause this difference in skin color, which should occur in time with each pulse. Choosing a region of interest (ROI) on the face is the initial stage in these methods. After measuring the ROI's color values for each frame, filtering and signal fusion are used to create a PPG signal. Finally, the PPG signal can be used to determine the heartbeat frequency that corresponds to the variation in skin color.

In this case, continuous vital sign monitoring is necessary to detect infections that could jeopardize a patient's health early on. Vital physiological signs, such as heart rate and respiration rate, can be routinely monitored to detect sleep apnea, depression, and other physiological problems. Nevertheless, conventional monitoring devices—which are usually connected by cables—may cause skin discomfort and damage in addition to restricting mobility, rendering them inappropriate for long-term monitoring. Nonetheless, contactless radar-based vital sign monitoring offers some advantages over traditional techniques. Radar signals, in contrast to those from cameras, are unaffected by skin tone or ambient light levels and can pass through a variety of materials. Radar systems don't require users to carry or wear any additional equipment, in contrast to wearable sensors. Radar devices can also be inexpensive, low-power, and privacy-preserving. A variety of radar types are currently being used for a broad range of healthcare applications, including assisted living, diagnostics, sleep monitoring, life detection and rescue, and many more, as a result of the scientific community's awareness of these intrinsic qualities.

II . LITERATURE SURVEY

Human vital sign parameters, such as pulse rate (PR) and respiration rate (RR), as well as soft biometric data including age, gender, skin color type, and body height, were proposed and implemented by Rizal et al. Our solution is based on a system-on-a-chip (SoC) device that offers tiny form size, real-time operation, and the ability to operate both FPGA and hard processors.

According to experimental data, our device's performance is 2.85 and 1.46 bpm for PR and RR, respectively, mean absolute error (MAE) when compared to clinical apparatus. On the other hand, we were not satisfied with the age and gender estimation findings for the soft biometric parameters measurement, which had an accuracy of 58% and 74%, respectively.

The objective of Tran et al. is to create a fully intelligent non-invasive vital-sign signal recognition using picture analysis with reference to clinical situations so as to extract values of blood pressure, heart rate, and breathing rate. The interesting bounding boxes like palm, face, and chest are found using the most sophisticated object identification technology, Yolov3. The Mosse algorithm then tracks these ROIs to increase processing efficiency. Next, the Pyramidal Lucas-Kanade and distant photoplethysmography techniques are employed to extract the motion signals (breath, pulse) and the tiny color shift generated by pulse, respectively. To create a clean bio-signal, digital signal processing is also utilized to remove unnecessary noise. Experiments have shown that our system can detect breath rate and heart rate in real time over large distances. Similar to the non-invasive blood pressure calculation method, the proposed deep learning strategy overcomes the dependence of the previous investigations on the high-speed camera. It conforms to two medical standards (the British Hypertension Society and the Association for the Advancement of Medical Instrumentations) for Systolic Blood Pressure (SBP) and Diastolic Blood Pressure (DBP) estimation. The root mean squared error and mean absolute error for SBP/DBP are 7.942/7.912 mmHg and 6.556/6.372 mmHg, respectively. The recommended technique continually measures blood pressure non-contact at 30 frames per second using a standard webcam. As a result, one may say that our method has uses in the medical industry.

A summary of the fields of data collection technology (hardware), image and signal processing (software), accuracy, and application is given by Selvaraju et al. [13]. While RGB cameras are used in controlled environments to continually monitor HR and RR, other vital signs remain unmonitored and need robust and accurate solutions. Accuracy is greatly influenced by the subject, camera, environment, and situation. Robust techniques grounded on deep learning, or DL, are desperately needed to counteract these effects. Furthermore, fusion-based methods can be used to increase reliability. It is feasible to explore a range of hardware and software parameter values to get the best outcomes for different circumstances. One possible use for cameras in relation to the COVID-19 pandemic would be to set them up for smart home health monitoring of individuals under quarantine. The Food and Drug Administration (FDA) in the United States has recently approved smartphone applications for therapeutic purposes, such as tinnitus. Considering this advancement, digital health may also include vital sign monitoring using a smartphone's camera. The transmitting (TX), receiving (RX), clock, RF synthesizer, digital circuit, analog-to-digital converter (ADC), single-chip microprocessor (MCU), and digital signal processor (DSP) components make up the FMCW radar system.

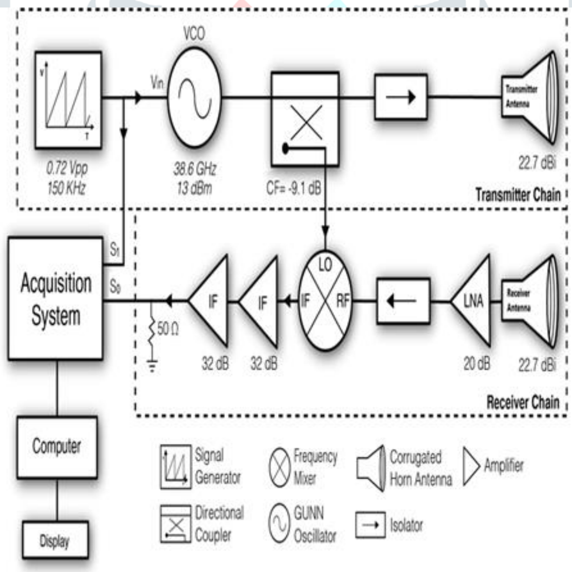


Fig.1: FMCW radar block diagram.

Through a transmitting antenna, the FMCW radar periodically broadcasts a chirped signal produced by a synthesizer with a frequency that grows linearly with time. Each transmitting chain has independent control over phase and amplitude. The intended frequency is produced by the RF synthesizer, which sounds like a chirping signal that varies with time. A low noise amplifier (LNA) amplifies the signal that the receiving antenna receives and correlates it with the mixer's local chirp.

Typically, the transmitted signal has a triangle or sawtooth waveform. Two orthogonal I/Q channels combine the RX and TX signals, and an intermediate frequency (IF) signal is produced via low-pass filtering. A single tone signal with a fixed frequency can be found in the IF signal. The fast Fourier transform (FFT) is applied to the IF beat signal once the IF signal has been received. Spectral peaks represent various subject separations. Each chirp signal's range FFT reflects a distinct distance at a given time, and the range FFT at a given time indicates how $\psi(t)$ in (6) varies over time. Several chirp signals are transmitted in the detection time range, which is equal to sampling D(t), in order to quantify the change of the vital signal with time. It is referred to be a frame period if D(t) is sampled every Tr. Consequently, phase extraction of distance FFT at continuous time can yield the sign information.

III . PROPOSED SYSTEM

Heart and breathing rate were previously calculated using ECG and other data in the system; however, with the rise in popularity of deep learning algorithms, the author has now added contactless vital sign estimate based on facial motion of the user. The suggested study uses phase-based motion processing to identify facial motions, which are subsequently retrieved as PPG (photoplethysmography) signals. The CNN method will be used to train these signals, and once trained, the model may be used to estimate heart and breathing rate from any human face motion signal.

The proposed work involves reading ten frames that contain human faces, detecting faces, extracting the region of interest (ROI) of faces, and extracting temporal and spatial features (current time and frame data). These features are then fed into the Phase-based Video Motion Processing (PVMP) algorithm, which generates PPG signals, which are then fed into a CNN model to predict heart and breath rate.

PPG Signals

PPG signals are a type of physiological signal that measures fluctuations in blood volume in peripheral blood vessels. PPG is a non-invasive method of tracking cardiovascular properties, including heart rate, blood oxygen saturation, and pulse waveforms. A light source, often an LED, is shone on the skin to generate the PPG signal. A photodetector is then used to identify any light that is transmitted or reflected back. Different blood types absorb light in different ways, making it possible to distinguish between variations in light intensity. These PPG signal intensity variations correspond to the pulsatile component of blood volume fluctuations that occur throughout each heartbeat.

Among other parts of the body, PPG signals can be recorded from the fingertip, earlobe, forehead, or wrist. The ideal measuring position will depend on the specific application and the physiological parameters to be measured. PPG signals are widely used in wearable technology and healthcare to track vital signs. They are commonly found in fitness trackers, smartwatches, and pulse oximeters. PPG signals can be used to detect alterations in arterial stiffness or abnormal heart rhythms. They also provide helpful details on heart rate and blood oxygen saturation levels.

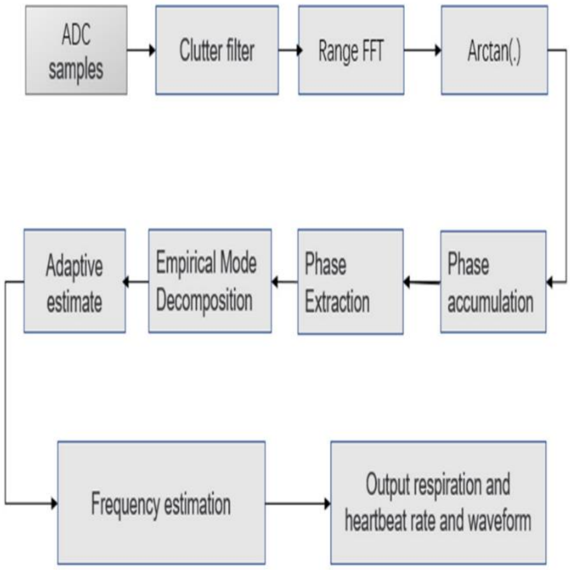


Fig-2: human heartbeat and respiration signal

Phase-based video motion processing (PVMP)

Analysis and comprehension of motion in video sequences can be achieved through the application of phase-based video motion processing. Its foundation is the notion that motion data can be derived from the video signal's phase component. Because it can handle a variety of motion types, such as translational, rotational, and complicated motions, this method has grown in favor. Decomposing a video clip into its individual frames is the first step in the process.

After that, each frame is converted into the frequency domain using methods like the Gabor or Fourier transforms. The local phase shifts in the video stream are represented by the phase component of the modified frames. Phase-based motion is achieved by examining the phase variations between successive frames. Motion between frames can be estimated via processing techniques. By measuring the local phase shifts and their magnitudes, this estimation is accomplished. The direction, speed, and magnitude of the motion can all be determined with the help of these measures.

One advantage of phase-based motion processing is that it can handle complex motion patterns that traditional approaches, such as block-based motion estimates, may find challenging. It has the ability to precisely record and show both local and global motion in a video clip. Furthermore, phase-based algorithms show less sensitivity to noise and image variations than intensity-based techniques do. Many industries, including action detection, video editing, video compression, and video surveillance, use phase-based motion processing. Among the tasks it enables are motion-based feature extraction, motion segmentation, and motion tracking.

CNN Model

Based on the available data, CNN is trained and tested by exposing each input voice to a series of convolution layers, each of which is controlled by a kernel, filter, rectified linear unit (ReLU), max pooling, fully connected layer, and SoftMax layer, which is used in conjunction with the classification layer in order to classify objects based on probabilistic values between [0,1]. The convolution layer is the primary layer that extracts features from a source speech and keeps the relationship between pixels intact by using small blocks of source data to learn the properties of speech.

This computation takes into account two inputs, such as source speech l(x,y,d), where x and y stand for the number of rows and columns, or geographical coordinates. A filter or kernel with a size comparable to the input speech is represented by the symbol F(kx, ky, d), and d is the dimension of the speech (in this case, d=3, as the source speech is RGB).

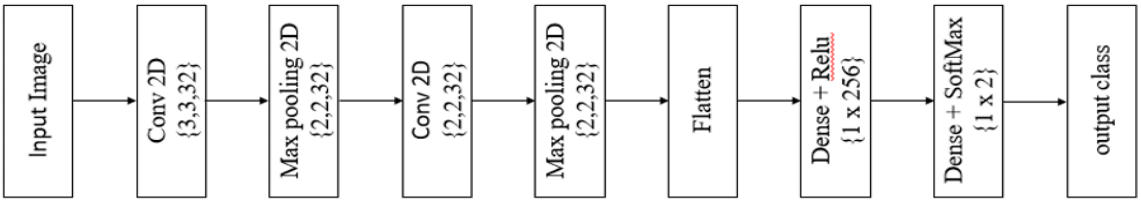


Fig. 2.1: convolution layer process

A feature map, with a size of C((x-kx +1), (y-ky +1),1), is the result of convolutioning the input speech and filter. Fig. 2(a) is an illustration of the convolution process. Assume for now that the input speech has dimensions of 5 by 5, and that the filter has dimensions of 3 by 3. Multiplying the input speech values by the filter values, as shown in Fig. 2(b), yields the input speech feature map. ReLU layer: Rectified linear units (ReLUs) are networks that use the rectifier operation for the hidden layers. This ReLU function is a straightforward computation that, in the case when the input value is larger than zero, returns the value supplied as input; otherwise, it returns zero. Mathematically, this can be expressed as follows using the function max(.) over the set of 0 and the input x:

Max pooing layer:
When there are larger-sized speeches, this layer reduces the amount of parameters. This process, which preserves the crucial information while reducing the dimensionality of each feature map, is known as subsampling or down sampling. In max pooling, the maximum element from the corrected feature map is taken into account.

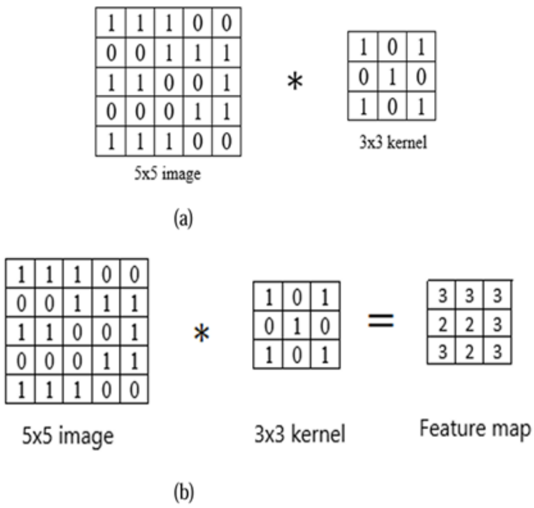


Figure 2.2: A convolution layer process example. (A) A 5 x 5 speech convolves with a 3 x 3 kernel.
(b) A map of involved features.

IV . RESULTS AND DISCUSSION

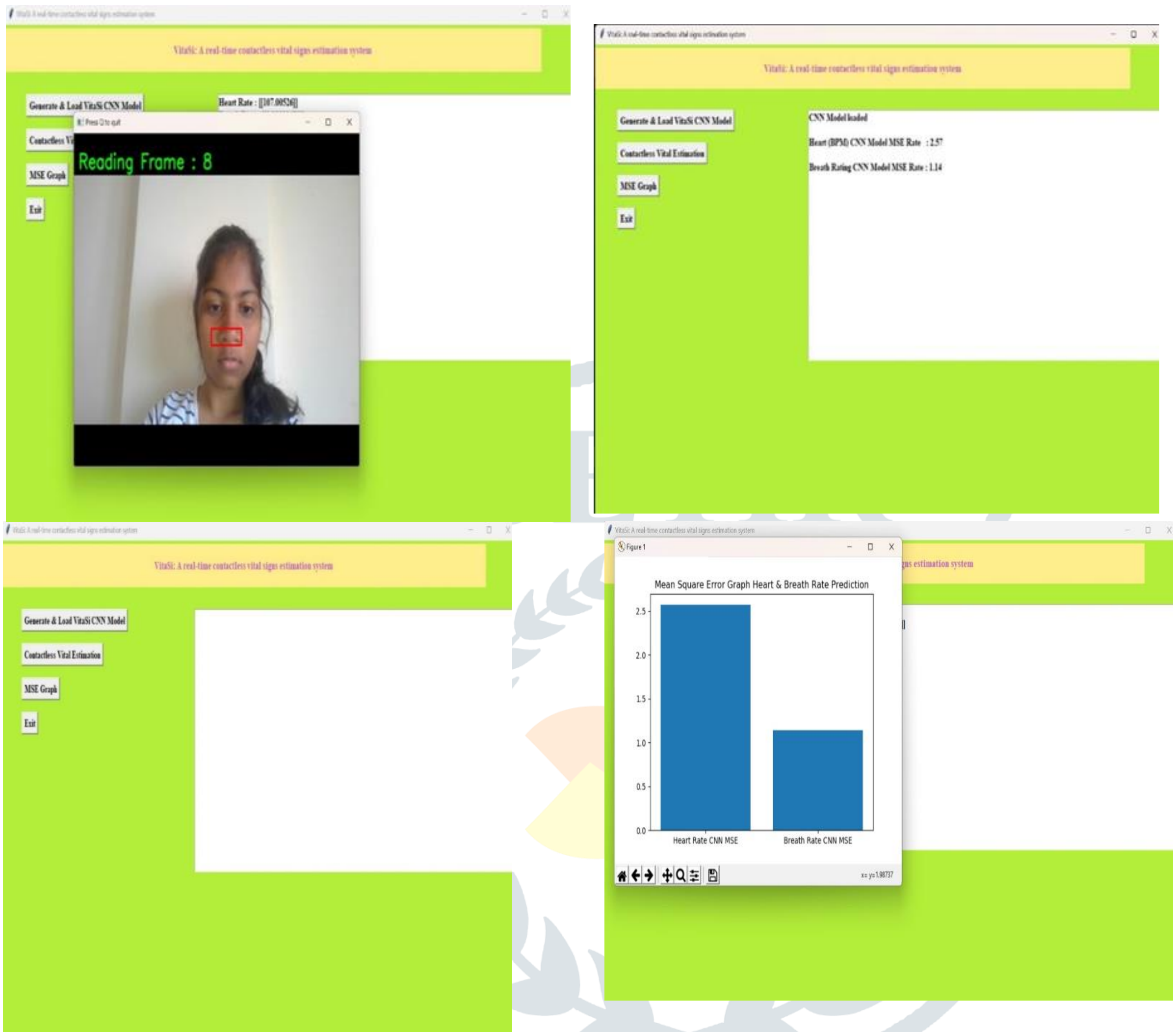
The project involves using the COHFACE dataset, which consists of 11 videos. We used the CNN algorithm to train the model and also extracted various features from these videos. The following modules will be used to implement the project.
The following modules have been built in order to accomplish this project; all of these features will be computed from WEBCAM.

- Generate & Load VitaSi CNN Model: This module is used to load the CNN model, which is capable of predicting breathing and heart rate.
- Contactless Vital Estimation: this module will launch WEBCAM, read ten frames, and use a CNN model to extract the PPG signal in order to estimate heart and breathing rate.

- MSE Graph: this module allows us to show the mean square error, or MSE, of the CNN model used to forecast heart and breathing rates. The prediction model is better the smaller the MSE.

Click the "Generate & Load VitaSi CNN Model" button on the top screen to generate and load the CNN model and see the screen below.

Click the "Contactless Vital Estimation" button to launch WEBCAM and estimate heart rate and breath rate. The CNN model has loaded on the screen above, giving us heart rate MSE of 2.57 and breath rate MSE of 1.14. The webcam in the above screen reads ten frames before predicting the heart and breathing rates, which are then updated and presented on the text area. From the above screen, we can see that the heart rate is 107 and the breathing rate is 0.13. Click the "MSE Graph" button to see the graph below.



In above graph x-axis contains type of prediction and y-axis contains MSE error value of CNN prediction.

Note: if no face shown to WEBCAM, then it will throw exception and stop executing.

V . CONCLUSION AND FUTURE SCOPE

The present study underscores the significance of monitoring vital signs, specifically heart rate (HR) and breathing rate (BR), in the context of patient care and disease prevention. Because contact methods like Electrocardiography (ECG) and Photoplethysmography (PPG) are accurate, they are frequently utilised. These techniques, however, can be uncomfortable for users and call for personal contact. In order to overcome these drawbacks, this work suggests using CNN for real-time contactless HR and BR estimate, which is based on PPG. There are a number of prospective areas that could be investigated more in the future.

To ensure the reliability as well as effectiveness of the contactless PPG-based approach, validation and accuracy studies can be carried out to contrast it with conventional contact approaches. Secondly, the accuracy of HR and BR estimate using PPG can be improved by improving the algorithms and signal processing methods. Third, there is potential to investigate the use of the contactless approach in non-medical and healthcare contexts, such as fitness tracking or wearable technology. Last but not least, there are intriguing opportunities to apply the contactless PPG-based approach outside of healthcare, such as in the fields of stress management and overall wellbeing.

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