Comparative Study of Biomedical Physiological based ECG Signal heart monitoring for Human body

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Abstract

Cardiovascular disease the major challenges in the current 21st century in terms of health care and related to diagnostic developments. In this pandemic COVID-19 scenario, the cardiovascular disease or non-cardiovascular disease has been increased like cardiac arrest or silent heart attack. According to WHO has guidelines, it is set to reduce 25% overall mortality rate due to cardiovascular disease upto 2025 on the priority basis kept as prevention and control. Some techniques developed for heart rate estimation from multimodal physiological signals namely ECG, AB, and PPG, EEG, EMG and EOG etc. are the part of cardiovascular and non-cardiovascular signals have been reviewed.

Keywords

ECG, Arterial Blood Pressure (ABP), Electroencephalogram (EEG), Electro-oculogram (EOG) and Electromyogram (EMG)

1. Introduction

Human body consists of various major parts and heart [1] plays the main important role for the body to be alive else it is dead body. If other part of the body is infected but not related to heart then with that problem the person can survive or alive with special care as per the infected disease. The heart is the main system of the body to pump the blood throughout the body due to contraction of muscles. Electrical signals [2,3] generated through the body, provoking variations in the electrical potential of skin surface. These signals (ECG related to heart) are captured with the help of electronics devices like electrode and related measurement equipment. At first these signals captured in 1887 for human ECG [4] signals, the electrical activity of the heart is recorded. But now we have so many approaches to measure or record ECG signals in three ways as ECG methods [3,5]-

1.in-the-person
2.on-the-person
3.off-the-person

When a person report for treatment or surgery then if certain designed equipments are used inside the human body or ingested in the form of pills are well known as in-the-person category. If some electrodes or sensors are used over the human body or touch the outer skin for ECG measurements is well known to be on-the-person category and majorly used devices for ECG monitoring. In case of off-the-person category it is found that minimal skin contact or ECG without skin contact. It is based on the capacitive devices which measures the electric field changes induced by body allow ECG measurement at distances of 1cm or more even with the help of sensors[6,7].

Various tests are used to diagnose heart disease[6-8] and doctor enquires about personal and family medical history [8,9]and records the present and past symptoms. Based on the assessment enquiries doctor recommend for the related laboratory test. These tests may be invasive or non-invasive test. If laboratory tests are taken with the help of instrument inserted into the body is called non-invasive otherwise it is understood invasive tests[8-10].

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Types of Test:

1. Invasive test
2. Non-Invasive Test

Invasive Test: It is a medical practice of cut skin and insert into the body opening for test using instruments while doing such types of test [10, 11] biopsy, endoscopy, and cryotherapy etc is required.

Non-Invasive test: Non-invasive disease does not damage other organs of human body [2,5]. In this case when there is no need of tools that break the skin physically enter the body the skin. For instances [4, 5, 9] x-ray, CT Scan, MRI, ECG. Hearing aids, external splints and casts fall under this category as a related device.

Cardiac Catheterization: common procedure that helps to diagnose heart disease [7,8] it can also be used to treat heart disease by opening blocked arteries with balloon angioplasty and stent placement.

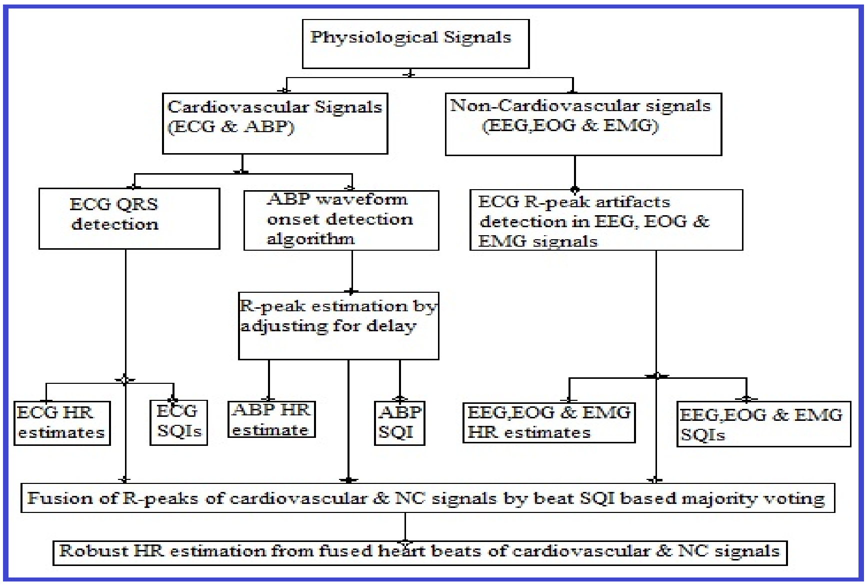

Figure 1: Layout of Physiological signals with ECG artifacts detection for cardiovascular/non-cardiovascular [7, 8]

Some physiological [9-11] signal recognizes emotions due to its instant reaction and human as body structure is complex. So various related physiological [12-14] signals like HR, HVR, ECG, EEG, blood pressure etc. This type of signals travel into multichannel [15-19] as single channel has its own limitation.

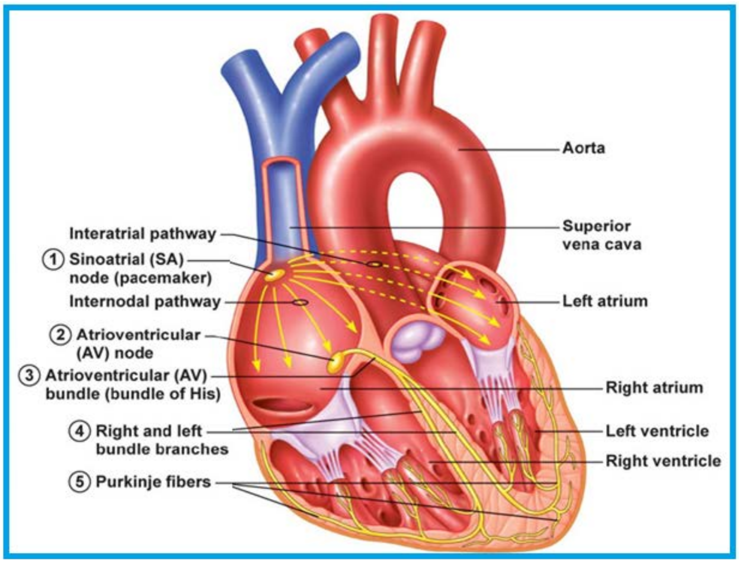

Figure 2: Anatomy of Heart (internet sources) [8-10]

These signals can be classified through the classifier [16,18] as SVM-support vector machine. Multimodal physiological [10-12] signals are helpful to monitor continuously the health of patients either in ICU or at home at night. In high-tech hospitals [9, 11] there are the availability of intelligent bed system [11-13] for the patients whom automatically health monitors[12,14] and send the signal to the cloud server. Mainly focused signals are Electrocardiogram (ECG), Arterial Blood Pressure (ABP), Electromyogram (EMG), Electroencephalogram (EEG) and Photoplethysmogram (PPG)[11,12,15] etc. The signals directly helpful to monitor the heartbeat are related to cardiovascular and these are ECG, ABP and PPG etc and those physiological signals are indirectly connected or helpful are called non-cardiovascular signals such as EEG,EMG and EOG etc.

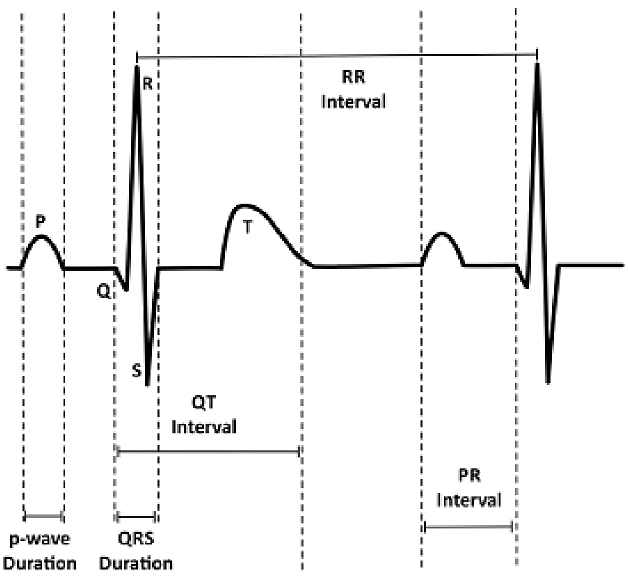

Figure 3: Cardiac cycle in an ECG Signal [11, 14]

In Figure 3, it represents the heart signal observed as ECG signal and shows some up-down lines like half sinewave and sharp peak like sawtooth waveform as monitored in electrons analog signals. Basically these have been termed as the English alphabets namely P; Q; R; S; T; U. These are the heart monitored ECG signals and termed as P-wave, T-wave, U-wave, and QRS complex wave. If we go through all the waves shows unique patterns. So these have defined as P-wave as atrial depolarization, T-wave as ventricular repolarization, U-wave as Papillary muscle repolarization and the last one is QRS complex wave as ventricular depolarization.

2. Literature

Eduardo Jose da S. Luz, et al [1], authors described in their work about the current scenario state-of-art-methods of ECG-based automatic abnormalities heart beat classification, ECG signal processing heartbeat segmentation techniques, feature description methods and learning algorithms used.

Tian Zhou, et al [3], results have compared the performance of different classifier, sensor fusion schemes, physiological modalities such as heart rate variability, electrodermal, and Electroencephalogram (ECG), (single vs multiple based on the prediction). In this case multisensors approach is used and got the individual performance which predicts cognitive workload levels of 83.2% of the time during basic and complex surgical skills tasks.

Wei Wei, et al, [4], proposed a decision level weight fusion strategy for emotion recognition in multichannel physiological signals. Study focused on the four types of physiological signals includes EEG, ECG, Respiration Amplitude RA, and Galvanic Skin Response GSR. Various analysis domains have been used in physiological emotion features extraction. Secondly, adopted feedback strategy for weight definition, according to recognition rate of each emotion of each physiological signal based on Support Vector Machine, SVM classifier independently.

Luis J.Mena et.al [5], developed wearable ECG monitoring device integrated with self-designed wireless sensor for ECG signal acquisition. It is native purposively designed smartphone application based on machine learning techniques, for automated classification of captured ECG beats from aged people.

Deger Ayata, et al [8], proposed a novel emotion recognition algorithm from multimodal physiological signals for emotions aware healthcare systems. The physiological signals are collected from respiratory belt RB, photoplethysmography PPG, and fingertip temperature FTT sensors. The collection of the signal is done by wearable technologies. The results shows improved accuracy for arousal (69.86 to 73.08%) and from (69.53 to 72.18%) for valence. This is due to the multiple sources of physiological signals and their fusion increases the accuracy rate of emotion recognition.

Xiaowei Zhang, et al [9], proposed a regularized deep fusion of kernel machine framework for emotion recognition based on multimodal physiological signals. Experimental study shows two benchmark datasets which improve the subjects-independent emotion recognition and compared to single-modal classifiers or other fusion methods.

Chen Wang et al [10], proposed various methodologies to monitor or detection of heart rate (HR) using human face recording. This is done as there is motion in the cardiovascular activities or subtle color changes as the method used.

Syem Ishaque et al [11], restricted the physiological signals ECG, EDA (Electrodermal Activity), PPG (photoplethysmography), and respiration (RESP) analyzed the heart rate variability between each heartbeat w.r.t time. Various analysis of various research work have been analyzed HRV associated with morbidity and stress. Detection of HRV in motion is far from perfect situations involving exercise or driving reported accuracy as high as 85% and as low as 59%. This can be improved with the advancement of machine learning techniques.

Fanny Larradet et al [12], focused on the methodological issues in real life data collection in the wild based on physiological signals like emotion recognition. In the paper common technique used to induce emotions for the physiological dataset creation to compare with existing dataset of real-life applications. Author also proposed a set of categories visual tool called Graphical assessment of real-life application-focused emotional dataset (GARAFED) and compared with existing physiological datasets for EMSR in the wild.

Quentin Meteier et al [13], discussed about the workload and task of drivers requested to regain the control of the car while performing the secondary task. In future, no longer of primary task for the driver as the automation of cars introduced. Measuring drivers workload continuously essential to support the driver and hence to limit the no. of accidents in takeover situations. For this purpose machine learning techniques is used to evaluate and classify the workload in real-time.

Haoran Xu et al [17], prepared the system for the hospital general ward to monitor wirelessly (wearable and artificial intelligence) using physiological signals (ECG, RESP and transmit data wireless). The system consists of multi-sensor wearable device, database servers and user interface. Hospital needs to be highly integrated with the existing hospital information system and then explored the set of processes of physiological signals acquisition, storage, analysis and combination with the e-health records. Once the system is implemented in the general ward of the hospitals and starts collecting more than 1000cases from the clinics and so continues the whole system repeatedly to give the clinic feedback. With this system helps in reliable physiological monitoring of patients of general ward in the hospitals and generates more personalized pathophysiological signals/information to diagnose the disease and treatment form continuously monitored physiological data.

Throughout the latest 20 years, beat screens (HRMs) have become a for the most part used guide for a grouping of employments [18]. The improvement of new HRMs has in like manner progressed rapidly during the latest two decades. Despite beat (HR) responses, look at has starting late revolved more around beat capriciousness (HRV).

Existing approach for separating heart-related signs fall under two classes: wearable sensor advancements [19] and non-contact (fusing) structures. The conventional framework for checking beat surveyed the spikes of the potential made by heart at each weight beat for example electrocardiogram, or ECG. Physiological estimations, for example, ECG signals, are unbelievable considering the way that they are obliged by means of modified actuations of the autonomic unmistakable structure (ANS).

In any case, existing sensors that can separate these signs require physical contact with subject's body, and causes impedance with the client experience. Various wearable advances, for example, a versatile ECG contraption, worn as a chest band holds the sensor focused over the heart, may move the readings remotely to the host PC. Unfortunately, the chest band is ungainly when worn for extended periods. It has a task to do in helpful and practice settings, at any rate it's unquestionably not a feasible choice for consistent use. Subsequently, wristband or a sharp have inadequacies [20].

3. Inferences from Literature

Eduardo Jose da S. Luz, et al [1], The depth and detailed discussion has been concise related to limitations, drawback methods found the literature which concludes and remarks the same and future challenge. Finally authors proposed the evaluation workflow process.

Table 1

Typical feature of a normal ECG signal, with a cardiac frequency of 60beats per minute of healthy adult

Feature	Normal Value	Normal Variation (+ve/-ve)
P-wave	110ms	20ms
PQ/PR interval	1160ms	40ms
QRS width	100ms	20ms
QT interval	400ms	40ms
Amplitude of P	0.115mv	0.005mv
Amplitude of QRS	1.5mv	0.5mv
ST level	0mv	0.1mv
Amplitude of T	0.3mv	0.2mv

Source: [2] G. D. Clifford, F. Azuaje, P. McSharry, Advanced Methods and Tools for ECG Data Analysis, 1st ed., Artech House Publishers, 2006.

Tian Zhou, et al [3], Authors discussed about the frame work leverages wireless sensors to monitor surgeons' cognitive load and predicts their cognitive load and predict their cognitive states. Continuous multiple physiological modalities had simultaneously recorded for 12 surgeons performing surgical skill task on the validated da Vinci Skills Simulator.

Table 2

Performance of six different classifiers and chance as base predictor

Classifier	Accuracy	Precision	Recall	F1 Score
Chance (flip a coin)	0.487	0.435	0.509	0.470
Support Vector Machine, SVM	0.773	0.810	0.641	0.716

Decision Trees, DT	0.714	0.694	0.641	0.667
Random Forest, RF	0.739	0.739	0.641	0.687
Extra Trees, ET	0.756	0.800	0.603	0.688
Gradient Boosting Trees, GBT	0.731	0.784	0.547	0.644
Adaboost, AB	0.681	0.653	0.603	0.627

Table 3

Performance of different modalities for Individual case

Classifier	Accuracy	Precision	Recall	F1 Score
EEG	0.782	0.755	0.755	0.755
EDA	0.479	0.395	0.321	0.354
HRA	0.504	0.442	0.434	0.438
MOV	0.664	0.710	0.415	0.524
EMG	0.580	0.526	0.566	0.545

Wei Wei, et al, [4], The experiments on the MAHNOB-HCI database show the highest accuracy. The result also provide evidence and suggest a way for further developing a more specialized emotion recognition system based on multichannel data using weight fusion strategy.

Table 4

The size of each set of each emotion

Emotion	Sample Set	Training Set	Test Set
Sadness	69	31	98
Happiness	86	31	55
Disgust	57	31	26
Neutral	112	31	81
Fear	39	31	8

Table 5

Detailed number of correctly recognized data and recognition rate under various physiological signals

Signal/ Emotion	Sadness	Happiness	Disgust	Neutral	Fear
Test Set	38	55	26	81	8
EEG	25 (65.79%)	42 (76.36%)	13 (50.00%)	70 (86.42%)	5 (62.50%)
ECG	21 (55.26%)	37 (67.27%)	18 (69.23%)	63 (77.78%)	4 (50.00%)
RA	17 (44.74%)	30 (54.55%)	12 (46.15%)	51 (62.96%)	3 (37.50%)
GSR	18 (47.37%)	29 (52.73%)	13 (50.00%)	56 (69.14%)	4 (50.00%)
Identity Matrix	25 (65.79%)	43 (78.18%)	18 (69.23%)	72 (88.89%)	5 (62.50%)
Diagonal Matrix	**28 (73.68%)**	**47 (85.45%)**	**20 (76.92%)**	**75 (92.59%)**	**6 (75.00%)**

Table 6

MAHNOB –HCI database recorded signals

Emotion Data Modalities	Frequency
32-channel EEG	256 Hz
3-channel ECG	256 Hz
1-channel RA	256 Hz
1-channel GSR	256 Hz
1-channel Skin Temp (SKT)	256 Hz

Face and Body Video	6 cameras, 60f/s
Eye Gaze	60 Hz
Audio	44.1KHz

Luis J.Mena et.al [5], When tested on 100older adults, the monitoring system discriminated normal and abnormal ECG signals with a high degree of accuracy 97%, sensitivity 100%, and specificity 96.6% With further verification, the system could be useful for detecting cardiac abnormalities in the home environment and contribute to prevention, early diagnosis, and effective treatment of cardiovascular diseases, while keeping costs down and increasing access to healthcare services for older persons.

Table 7
Performance summary of the ECG sensor device

Technology	**Low-power microchip 8-bit AVR RISC-Based Microcontroller**
Supply Voltage	3.3V
Input Impedance	100M-ohm
Frequency Response	Range 0.1Hz and Internal 8Mhz calibrated Oscillator
Common Mode Rejection Ratio	More than 90dB
Gain	45
Sampling Rate	9.6KHz
Data Bit-width	8bits
Supply Voltage	3.3V

Table 8
Total test performance of the mobile personal health monitor (PHM) system

Technology	**Low-power microchip 8-bit AVR RISC-Based Microcontroller**
Supply Voltage	3.3V
Input Impedance	100M-ohm
Frequency Response	Range 0.1Hz and Internal 8Mhz calibrated Oscillator
Common Mode Rejection Ratio	More than 90dB
Gain	45
Sampling Rate	9.6KHz
Data Bit-width	8bits

Table 9
Total test performance of the mobile personal health monitor (PHM) system

Evaluation Metrics	**Values (%)**
Sensitivity	100
Specificity	96.6
Accuracy	97
Precision	81.3

Deger Ayata, et al [8], The study shows a framework for emotion recognition using multimodal physiological signals from RB, PPG, and FTT. The paper concluded that the decision level fusion from multiple classifiers improved the accuracy rate of emotion recognition both for arousal and valence dimensions.

Table 10

Selected classifier and optimized hyper-parameters for PPG, RB, and FFT signals

Data source	Classifier	Feature set	Window duration	Window overlap
RB	Random Forest	FS-14	3 s	Overlap
PPG	Random Forest	FS-10	8 s	No-overlap
FTT	Random Forest	FS-10	5 s	Overlap

Table 11

Single modality and decision level fusion accuracy results

Signal source	Arousal Accuracy %	Valence Accuracy %
Respiratory Belt	71.32	70.62
PPG	68.59	70.23
FTT	69.68	67.73
Fused	73.08	72.18

Xiaowei Zhang, et al [9], Final fusion representation exhibits higher class-separability power for emotion recognition.

Table 12

Data dimension output of each module of the RDFKM Framework for each modality during the training phase on DEAP and DECAF datasets

Signal source	Arousal Accuracy %	Valence Accuracy %
Modalities	EEG,EMG,GSR,RES	MEG,EMG,EOG,ECG
Kernel	1200 x 1200	924 x 924
Embedding Layer	1200 x 100	924 x 100
FCN	64 x 1200	64 x 924
Intermediate Fusion layer	64 x 1200	64 x 924
Modalities	EEG,EMG,GSR,RES	MEG,EMG,EOG,ECG

Chen Wang et al [10], Several other approaches have been proposed as signal processing and machine learning. The algorithms analyzed and compared with the public database MAHANOB-HCI.

Table 13

Obtained performance for the best method at each stage

Stage	M (SD)/bpm	RMSE/bpm
Face video processing (extracted skin area)	5.34 (14.98)	15.05
Blood volume pulse signal extraction (independent component analysis)	4.09 (13.37)	13.56
Heart rate computing (peak detection)	3.01 (12.14)	12.23

Note: Mean error (M)-Performance measured; Standard Deviation (SD), RMSE(Root mean squared error) ; ρ-correlation co-efficient

Quentin Meteier et al [13], The author concluded a high level of drivers' mental workload can be accurately detected while driving in conditional automation based on 4-min recordings of respiration and skin conductance.

Table 14
Best score for each combination of selected signals (with a segmentation level of 1)

Selected signals	Best Classifier	Best Accuracy [Mean (SD)]
EDA	RF	0.73 (0.15)
ECG	RF	0.89 (0.09)
RESP	RF	0.88 (0.15)
EDA+ECG	RF	0.89 (0.09)
EDA+RESP	RF	0.89 (0.13)
ECG+RESP	MLP	0.94 (0.06)
EDA+ECG+RESP	SVC/MLP	0.92 (0.09)

4. Conclusion

I have studied last 6years paper and their linked referenced papers too previously cited paper in the literature papers. From all those papers it has been concluded that various types of physiological signals, various parameters as per the papers have been reviewed. The physiological signal (ECG) has been used to detect for some abnormalities in heartbeat classifications, segmentation techniques, and feature descriptions and learning algorithms used. In some papers different datasets used, different modalities, signal extraction and classifiers used, discussion of wearable technologies, and surgical skill task validated with da Vinci Skills Simulator. With different modalities signals found results to individual accuracy and precision four types of physiological signals includes EEG, ECG, Respiration Amplitude RA, and Galvanic Skin Response GSR. Various analysis domains have been used in physiological emotion features extraction.

5. Acknowledgment

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