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Analysis of ECG Signals Recorded Using Different Stimuli from Patients in Intensive Care Unit: A Case Study

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Abstract

Intensive Care Units (ICUs) are more difficult and complex areas of hospital as treatment and care. In these units, the patients are monitored continuously with a bedside monitor for respiration, O_2 saturation and pulse information. However, this information, which is periodically noted on the patient observation papers, may not represent a definite diagnose/follow up about the patient's health condition in all times. Therefore, in order to assist the physician in these units where the diagnosis/follow up is important, attributes are extracted from ECG signals easy-to-obtain by using signal processing methods. ECG signals were obtained from 3 patients at different days. Attributes were analyzed statistically to see if the patient reacted to oral/touch stimuli and to monitor his / her health condition. As a result, it was possible to evaluate the coma patients' response to stimuli and to follow-up for improving physiological well-being using ECG signals.

Key words: intensive care units, electrocardiogram, heart rate variability, sound stimuli, patient follow-up

1. Introduction

Consciousness is that the person is aware of himself/herself and what is happening around him and can adapt to new stimuli. Evaluation of the patient's consciousness state is important for neurological evaluation. Consciousness is a factor that affects the stages of patient evaluation and treatment. Neurological assessment requires patient assistance because motor and sensory evaluation cannot be performed for patients who are unable to respond to the given commands [1-3].

Consciousness level is not directly measured. It is measured according to the patient's response to stimuli. In the assessment of consciousness, firstly oral stimuli are given to the patient (such as how he/she is or asking for personal information). If the patient is unable to speak, he/she may be asked to respond with head shaking and eye movements. The patient's motor response is observed with intense but non-destructive painful stimuli such as trapezeus compression [1,3]. Consciousness levels are shown in Figure 1. The changes between these levels may occur suddenly or slowly. In coma, the patient's eyes are closed, do not response to environmental stimuli and do not have spontaneous movements [3].

Electrocardiography is the process of recording the electrical activity of the heart for a period of time using electrodes placed on the body. These electrodes detect small electrical changes in the

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skin caused by the depolarizing heart muscle at each heartbeat. In the conventional 12-lead Electrocardiogram (ECG), ten electrodes are placed on the patient's chest surface. Then the magnitude of the electrical potential of the heart is measured at twelve different derivations and recorded over a period (usually 10 seconds). In this way, the overall magnitude and direction of cardiac electrical depolarization is captured. As a result, the ECG signal is generated as a graph of time versus voltage.The ECG can be used to measure heart rate and rhythm, the size and location of the heart chambers, any damage to the heart muscle cells or conduction system, the effects of heart medications [4]

Clinical scales are susceptible to problems of sensitivity, specificity, subjectivity and interrater reliability. This leads to a misdiagnosis of up to 40% and consequences associated with inappropriate treatment decisions [5]. Wieser et al. reported that they used objective measurements including physiological and neurological signals to measure the consciousness status of 8 patients (5 females, 3 males). They conducted a linear retrospective regression analysis and concluded that the 13 variables obtained were enough to define 74.7% of the variability in the score. They used ECG signals in their studies. The frequency bands of the ECG were analyzed, and RMS and standard deviation values were calculated [5].

In the literature, ECG signals have been obtained to determine the stress experienced by drivers [6] or to examine stress levels [7]. Because ECG signals are easier to obtain and analyze than other physiological signals. There are many studies performed by obtaining pulse information and ECG signals from patients in intensive care [8-11]. Most of these studies are for the aim of establishing or developing alarm systems [12-14]. The ECG reflects the electrical activity of the heart controlled by the autonomic nervous system. When a person faces a situation that causes stress, the sympathetic nervous system occurs dominant in the autonomic nervous system and increases the heart rate. With the parasympathetic system, the body is attained to balance by reducing the heart rate [15].

The aim of this study is to evaluate the contribution of ECG signals in the follow-up of for improving physiological well-being patients in coma in Intensive Care Units (ICU). For this reason, ECG signals were obtained from three coma patients on different days, during the interaction between the nurse and the family, and at rest. Attribute extraction is done from ECG signals. Thus, it was tried to obtain information about the patient's well-being. As a result, it was shown that patients react to their relatives and nurses even if they are in a coma and monitoring of their health status can be done with ECG signals.

Figure 1. Level of consciousness [3].

2. Materials and Method

2.1. Recording System

After obtaining the approval of the Ethics Committee for our study, ECG signals were examined in different scenarios on the days determined by the physician from three patients with Glasgow Coma Scale between 3-10. As shown in Figure 2, ECG recordings were obtained from single channel (derivation I) using Biopac MP-150 device with a sampling frequency at 1000 Hz. Records were taken at five events: rest, interaction with the family and nurse. ECG signals were recorded at approximately 35 minutes duration and the performed process was defined in the below flow chart. In the event of rest, no stimulus was given to the patient and the environment was kept as quiet as possible. During the interaction with the nurse, the patient wanted to make certain commands such as opening his eyes and moving his arm. During the interaction with the family, personal information of the family were shared with the patient and provided contact with patient's hands. Also nurse and relatives of patients spoke to patients. Table 1 shows the demographic information for patients analyzed in this study.

- 5 minutes of rest recording (first basal event)
- 5 minutes record during nurse interaction event
- Rest for 10 minutes (second basal event)
- 5 minutes recording during family visit (family interaction event)
- Repeat baseline for 10 minutes (final/third basal event)

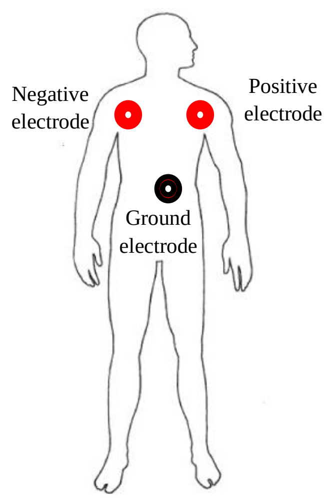

Figure 2. Electrode placement for ECG

Table 1. Demographic informations of patients

	Gender	Age	Stay Time (Day)	GCS
First Patient	Female	85	19	5
			40	5
Second Patient	Male	34	36	8
			47	10
Third Patient	Female	56	6	5
			34	6

2.2. Attributes

The ECG signals were filtered using 4^{th} Degree low pass butterworth filter with 100 Hz cut off frequency and 50 Hz notch filter (to eliminate mains voltage). Then, heart rate variability (HRV) was analyzed in time domain. HRV is calculated by evaluating at the time differences between each R wave in the ECG signal. In order to obtain HRV, it is necessary to find the time interval between the R waves of the QRS components in the ECG signals. The attributes obtained from ECG signals in this study are shown in Table 2. MATLAB program was used to extract the attributes.

Table 2. Attributes

Attribute	Definition
RR_STD	Standard deviation of R-R intervals
RR_RMS	Root mean squares of R-R intervals
AVG_BPM	Mean heart rate
ECG_MEAN	Mean value of ECG signal
ECG_STD	Standard deviation of ECG signal
ECG_RMS	Root mean squares of ECG signal

The standard deviation is a measure that uses the distribution of numbers in a series around the average of that series to summarize the spread of the data values and is calculated as follows:

$$std = \sqrt{\frac{\sum_{i=1}^{N}(X_i - \bar{X})^2}{N-1}} \tag{1}$$

Root Mean Square (RMS) returns the effective value of the signal and is the square root of the average of the sum of the squares of its elements (Equation 2). It is a statistical criterion used to measure the magnitude of varying amounts.

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {X_i}^2} \tag{2}$$

2.3. Statistical Test

The Wilcoxon signed rank test, which is a non-parametric test, was used for statistical analysis of the data obtained in order to observe the changes in the health condition of the patients. This method is used to observe the differences between the two related groups. For example, it is applied to analyze the changes in the average pulse in the ECG signal in case of first rest and family interaction [16]. In this study, it was used to examine changes in first rest-family, family-second rest, second rest-nurse, nurse-last rest events using obtained attributes. It was also used to investigate at the change in health status of patients in the ICU. In this study, Wilcoxon signed rank test was preferred because of the low number of data and not having normal distribution.

3. Results

The results were compared between events to measure the patient's response to the family and the nurse. The events examined are indicated below. Figure 3 shows the events that are compared. ECG recordings were taken on two different days from 3 patients. Thus, a total of 6 ECG signals were analyzed. Attributes were calculated separately for 5 events: first basal, family, second basal, nurse, third basal. Thus, 30 instances were obtained in the study. 28 samples were examined because the nurse and final resting conditions could not be analyzed for one patient.

- First basal-family interaction
- Family interaction-second basal
- Second basal-nurse interaction
- Nurse interaction-third basal

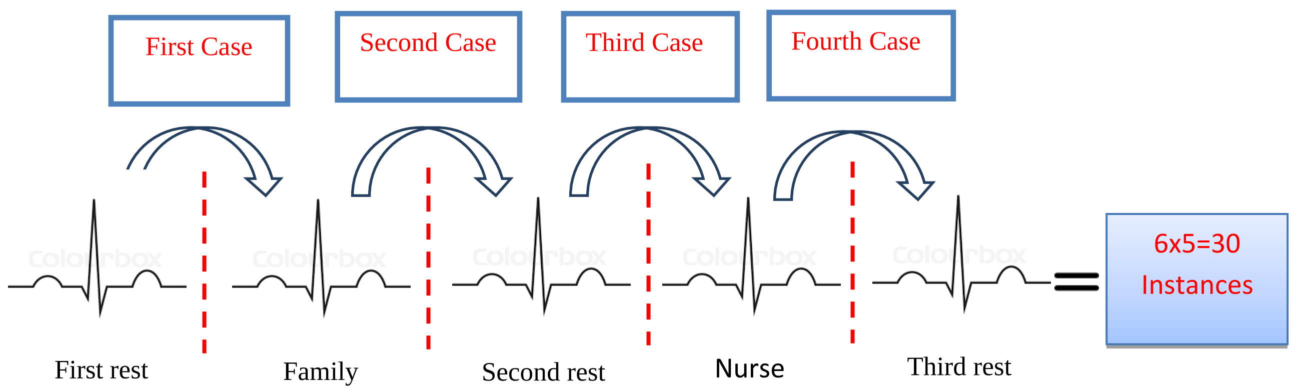

Figure 3. Comparison groups in statistical analysis

3.1. First basal- Family interaction events

Table 3 shows the descriptive statistics of the two events. This table contains information such as mean, standard deviation, maximum and minimum values of the obtained attributes. Table 4 shows the changes of attributes between events. Negative rank indicates the number of people who have experienced a decrease in related attribute value. The positive rank indicates the number of people who have experienced an increase in related attribute value. The same rank indicates the number of people who have unchanged value in related attribute. For example, according to the AVG_BPM attribute, there are 1 people whose average pulse decreases during communication with the family and 5 people whose average pulse increases during communication with the family. Mean heart rate increases during interaction with the family. When the average of AVG_BPM attribute is examined in Table 3, the mean pulse rate is 98 in the first basal event and 105 in the family interaction. It was observed that during the person's family talk and touching it is caused the heart to beat faster by activating the sympathetic system.

Table 3. Descriptive statistics for first basal-family interaction events

Attribute	Mean	Standard Deviation	Minimum	Maximum
First Basal Values				
RR_STD	3.849	8.659	0.01	21.50
RR_RMS	5.569	12.340	0.00	30.71
AVG_BPM	98.700	9.407	82.78	108.40
ECG_MEAN	0.022	0..309	0.00	0.08
ECG_STD	0.147	0.064	0.06	0.22
ECG_RMS	0.015	0.007	0.01	0.02
Family Interaction Values				
RR_STD	3.849	8.659	0.01	21.50
RR_RMS	15.280	27.895	0.02	71.02
AVG_BPM	105.415	15.575	82.87	130.42
ECG_MEAN	0.027	0.041	0.00	0.10
ECG_STD	0.148	0.062	0.07	0.22
ECG_RMS	0.015	0.007	0.01	0.02

Table 4. Ranks of First basal-family interaction events

	RR_STD	RR_RMS	AVG_BPM	ECG_MEAN	ECG_STD	ECG_RMS
Negative Rank[a]	0	2	1	4	3	3
Positive Rank[b]	0	4	5	2	3	3
Same Rank[c]	6	0	0	0	0	0

a. Family<first basal, b. family>first basal, c. Family=first basal

3.2. Family interaction-second basal events

Table 5. Descriptive statistics for family interaction-second basal events

Attribute	Mean	Standard Deviation	Minimum	Maximum
Family Interaction Values				
RR_STD	3.849	8.659	0.01	21.50
RR_RMS	15.280	27.895	0.02	71.02
AVG_BPM	105.415	15.575	82.87	130.42
ECG_MEAN	0.027	0.041	0.00	0.10
ECG_STD	0.148	0.062	0.07	0.22
ECG_RMS	0.015	0.007	0.01	0.02
Second Basal Values				
RR_STD	3.849	8.659	0.01	21.50
RR_RMS	2.012	3.638	0.01	9.06
AVG_BPM	105.761	17.464	84.37	134.45
ECG_MEAN	0.028	0.041	0.00	0.10
ECG_STD	0.149	0.062	0.07	0.22
ECG_RMS	0.015	0.007	0.01	0.02

Table 6. Ranks of family interaction-second basal events

	RR_STD	RR_RMS	AVG_BPM	ECG_MEAN	ECG_STD	ECG_RMS
Negative Rank[a]	0	5	2	2	2	2

Positive Rank[b]	0	1	4	4	4	4
Same Rank[c]	6	0	0	0	0	0

a. Family>second basal, b. Second basal>family, c. Family=second basal

3.3. Second basal-nurse interaction events

Table 7. Descriptive statistics for second basal-nurse interaction events

Attribute	Mean	Standard Deviation	Minimum	Maximum
Second Basal Values				
RR_STD	4.535	9.497	0.01	21.50
RR_RMS	2.411	3.917	0.01	9.06
AVG_BPM	100.023	11.591	84.37	109.95
ECG_MEAN	0.032	0.044	0.00	0.10
ECG_STD	0.151	0.069	0.07	0.22
ECG_RMS	0.016	0.008	0.01	0.02
Nurse Interaction Values				
RR_STD	4.535	9.497	0.01	21.50
RR_RMS	1.743	2.874	0.00	6.65
AVG_BPM	105.929	22.882	80.60	141.70
ECG_MEAN	0.027	0.032	0.00	0.07
ECG_STD	0.152	0.063	0.08	0.22
ECG_RMS	0.015	0.007	0.01	0.02

Table 8. Ranks of second basal-nurse interaction events

	RR_STD	RR_RMS	AVG_BPM	ECG_MEAN	ECG_STD	ECG_RMS
Negative Rank[a]	0	4	3	2	3	3
Positive Rank[b]	0	1	2	3	2	2
Same Rank[c]	5	0	0	0	0	0

a. nurse<second basal, b. nurse>second basal, c. nurse=second basal

3.4. Nurse interaction-third basal

Table 9. Descriptive statistics for Nurse interaction-third basal events

Attribute	Mean	Standard Deviation	Minimum	Maximum
Nurse Interaction Values				
RR_STD	4.535	9.497	0.01	21.50
RR_RMS	1.743	2.874	0.00	6.65
AVG_BPM	105.929	22.882	80.60	141.70
ECG_MEAN	0.027	0.032	0.00	0.07
ECG_STD	0.152	0.063	0.08	0.22
ECG_RMS	0.015	0.007	0.01	0.02
Third Basal Values				
RR_STD	4.535	9.497	0.01	21.50
RR_RMS	2.472	4.241	0.01	9.83

AVG_BPM	97.735	11.158	79.66	107.69
ECG_MEAN	0.028	0.035	0.00	0.08
ECG_STD	0.146	0.064	0.07	0.21
ECG_RMS	0.015	0.007	0.01	0.02

Table 10. Ranks of Nurse interaction-third basal events

	RR_STD	RR_RMS	AVG_BPM	ECG_MEAN	ECG_STD	ECG_RMS
Negative Rank[a]	0	0	4	2	4	4
Positive Rank[b]	0	5	1	3	1	1
Same Rank[c]	5	0	0	0	0	0

a. nurse>third basal, b. nurse<third basal, c. nurse=third basal

4. Discussion

When Table 5 and Table 6 were examined, it was observed that patients' heart rate increased after family visit. In the RR_RMS attribute, there was a significant decrease in rest after the family (second rest). The RMS value of the ECG signal decreased at second rest. When Table 7 and Table 8 are examined, it is seen that nurse interaction has a calming effect due to decreases in standard deviations. Thus, it can be thought that nurse interaction increases parasympathetic activity. Because they are experienced, they have an important role in healing the patient.

In addition, the first patient was evaluated as GCS 5 on the 19th day and on the 40th day. On day 19, the pulse rate was around 80 bpm (beat per minute), while on day 40 it was about 100 bpm. In addition, while the ECG_STD attribute was 0.09, it was around 0.06 on day 40. The standard deviation of the ECG wave was reduced. She had a higher heart rate on day 19 and a more regular ECG wave on day 40. However, the standard deviation of R waves (RR_STD) increased approximately 20-fold compared to day 19. With these data, it is seen that the patient has more irregular heartbeat, ie the patient's health condition does not improve.

When second patient was evaluated, the GCS was 8 on the day 36 and the GCS was 10 on the day 47. The average pulse was 130 bpm on day 36, while it was around 108 bpm on day 47. The standard deviation of R waves (RR_STD) 50 times lower on day 47 compared to day 36. In other words, it can be evaluated that the patient's health condition improves because he has more regular heartbeats and a lower pulse rate.

The third patient was evaluated as GCS 5 on day 6 and GCS 6 on day 34 in the ICU. The average pulse was 105 bpm on day 6 and 95 bpm on day 34. Although the standard deviation of ECG waves and the standard deviation of R-R waves are similar for day 6 and day 34, RR_STD decreased by 1.26 times on day 34. For this patient, whose consciousness level increased, her health condition was in the direction of recovery.

Conclusions

In this study, 3 patients with GCS 3-10 hospitalized in the ICU were examined with ECG signals recorded in different scenarios on different days. The main conclusions of the study, the changes in the health condition of the patients can be defined according to the attributes obtained from ECG signals recorded in the proposed scenarios of comatose patients. In addition, it has been shown that patient follow-up can be easily performed using ECG signals. Attributes of ECG signals and consciousness levels were correlated to obtain information about the patient's condition to help the physician. This is a case study carried out with 3 patients. Henceforward, it is planned to increase the number of data and obtain more precise results in patient follow-up.

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