A STUDY ON EMOTION RECOGNITION METHOD BASED ON INTEGRATED GALVANIC SKIN RESPONSE AND HEART RATE VARIABILITY BY MACHINE LEARNING ALGORITHM; RANDOM FOREST

[1]HERMIN KARTIKA SARI, [2]SUNARNO, [3]KWARTARINI WAHYU YUNIARTI, [4]MEMORY MOTIVANISMAN WARUWU, [5]RONY WIJAYA

[1]Master Program of Engineering Physics, Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia
[2]Department of Nuclear Engineering and Engineering Physics, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia
[3]Faculty of Psychology, Universitas Gadjah Mada, Yogyakarta, Indonesia
[4]Laboratory of Sensor and Telecontrol System, Faculty of Engineering, Universitas Gadjah Mada, Yogyakarta, Indonesia
[5]Production House, Faculty of Medicine, Public Health, and Nursing, Universitas Gadjah Mada, Yogyakarta, Indonesia
E-mail: [1]hermin.kartika.s@mail.ugm.ac.id, [2]sunarno@ugm.ac.id, [3]kwartarini_psy@ugm.ac.id, [4]morymw@gmail.com, [5]rwijaya80@gmail.com

Abstract - In this paper, we introduce the emotional recognition method by merging the information from physiological signals and self-assessment. The changes in emotional states affect the activation of the autonomic nervous system (ANS). Several bio-parameters can be used to monitor Electrodermal Activity (EDA) due to the activation of the ANS, such as skin conductance and heart rate variability as physiological signals. It is measured to monitor the participants' emotional recognition while presenting the stimuli. After that, participants reported their emotional state by scaled the stimuli using the Self Assessment Manikin (SAM) as an instrument to obtaining ratings of the participants' emotional states of each stimulus. The random forest (RF) has been used for classification, it is considered one of the most accurate classifiers and gives an accuracy of 75% for four target emotions, namely Happy, Sad, Fear, and Relaxed.

Keywords - Emotion Recognition, Galvanic Skin Response, Heart Rate Variability, Random Forest Method

I. INTRODUCTION

Emotions play a vital role in daily life [1] as a fundamental component of learning, cognition, and human experience [1]. It is classified as primary emotions or secondary emotions, and positive emotions or negative emotions. Ekman, Parrot, Frijda, Plutchik, Tomkins, and Matsumoto show that there are few basic emotions that valid for all ages and cultural differences in **Error! Reference source not found.**[2]. Positive emotions such as contentment, amusement, happiness, interest, love, hope, gratitude, relief are further improved human health as well as work efficiency, while negative emotions such as sadness, afraid, anxiety, frustration, disgust, anger, fear [3] may cause health problems. The accumulation of negative emotions is one of the factors causing clinical depression [4].

Other classifications of emotions using multiple dimensions or scales based on arousal and valence and represented by Fig.1, the four-class model [4], or well known as a two-dimensional model by Russell [5]. The horizontal axis is the arousal dimension that indicates the intensity of the emotional states and ranges from low arousal to high arousal [6]. The vertical axis is the valence dimension that represents pleasantness and ranges from the negative valence to positive valence [6].

Year	Name	Basic Emotions
1971	Ekman	Anger, happiness, fear, surprise, disgust, sadness
1986	Frijda	Desire, happiness, interest, surprise, wonder, sorrow
2001	Parrot	Anger, fear, joy, love, sadness, surprise
2001	Plutchick	Acceptance, anger, anticipation, disgust, joy, fear sadness, surprise

Table 1. Basic Emotions Classification by Psychologists [2]

Emotions can affect human decision-making processes and the status of humans physiologically and psychologically [4].

It is transmitted in several modalities of human communication, like words, tone of voice, facial expression, body language, and bio parameters like skin conductance, heart rate variability, etc. The changes of bio-parameters as a reaction to the activation of the autonomic nervous system (ANS) [2].

Therefore, bio-parameters analysis can be a reliable method for emotion recognition because the change in emotional states is involuntary, and people are often not aware of them. Another advantage, it can be designed to be wearable and not obtrusive [7].

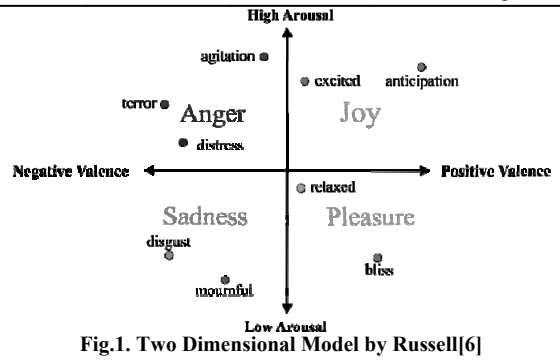


Fig.1. Two Dimensional Model by Russell[6]

The increased activity of sweat glands is an indicator of arousal and it is influenced by the activation of the ANS[8], especially the sympathetic nervous system (SNS) activity, driving human behavior on a subconscious level [9]. Sweating changes the ion balance through the skin pores, the skin resistance, skin conductance, to a constant electrical current change proportionally [9]. Because of this, Electrodermal Activity (EDA) suitable for the detection of the change of the emotional states.

Heart rate variability (HRV) was calculated to measure of beat to beat temporal changes of the heart rate and can be used for bio-parameter [2]. It is measured using Photoplethysmography (PPG). PPG monitors the Blood Volume Pulse (BVP) as the pulse-wave of the heart and the volume of the blood flowing through a vessel [2]. A PPG uses a light-emitting diode (LED) and a photodiode to record the pulse [2].

The classifier of the emotional states varies according to the researchers. Machine learning classifier is widely used by the researchers include Support Vector Machine (SVM), K – Nearest Neighbour (KNN), Decision Tree, Artificial Neural Network (ANN), and Random Forest.

There are recent studies concerning emotion recognition measuring physiological signals. Listed in Table 2are the used method, measure emotion, stimulus, classification method, and archived accuracy for recent works [2].

Given the importance of research towards emotion recognition, this paper proposes an approach for emotion recognition using bio-parameters (GSR and HRV) and is classified using machine learning; Random Forest (RF).

II. DETAILS EXPERIMENTAL

2.1. Participants

A total of 10 participants aged 21 – 23 years old (mean: 21.5 years old) were enrolled in this study. All participants were engineering students at the Gadjah Mada University, did not have any physical or mental illness and respiratory disease. They were informed about the aim of the study and the instructions of the experiment. When it was clear to the participants, they were led into the experiment room to be placed with the GSR sensor and HRV sensor. The participants were not allowed to do anything else during the experiment.

Table 2. Recent Studies Concerning Emotion Recognition Measuring Physiological Signals[2]

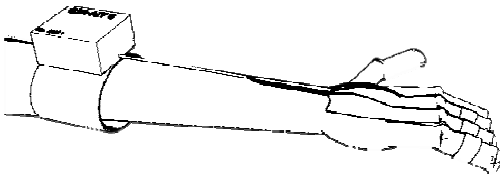
Year	Method	Emotion	Stimulus	Classification	Accuracy
2005	FR	Happy, angry, sad, surprised, scared, disgust, neutral	Video Clips	ANN	89%
2012	ECG	Excitement, erotica, disgust, fear, gore, neutral	Passive: IAPS Active: Video Games	Linear Discriminants, Leave-Out-Validation	52.41% passive, 78.43% active
2016	ECG	Sad, angry, fear, happy, relax	Movie Clips	SVM	56.9%
2016	EEG	Sad, scared, happy, calm	IAPS	KNN, SVM	55% KNN, 58% SVM

2.2. Experimental Setup

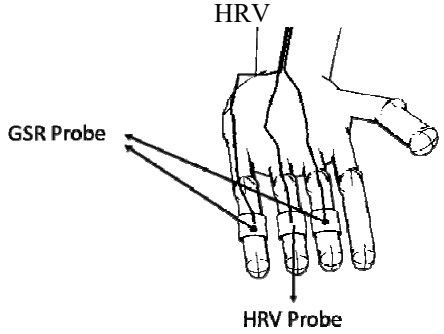
Detailed engineering design (DED) of integrated GSR and HRV is shown in Fig. 2. GSR probe is used in the index finger and the third finger, while the HRV probe is used in the middle finger.

2.3. Experimental Protocol

Fig.3 shows the experimental room protocol. The experimental room is a studio of 3 × 4 meters equipped with a soundproof layer, a TV 50 inch, a standardized seat for psychotherapy, an operator desk, and a speaker. The temperature of the room was set at 25°C.



(a) Detail Engineering Design Integrated GSR and HRV



(b) Detail Engineering Design Probe Integrated GSR and HRV

Fig. 2. (a) Detail Engineering Design Integrated GSR and HRV; (b) Detail Engineering Design Probe Integrated GSR and HRV

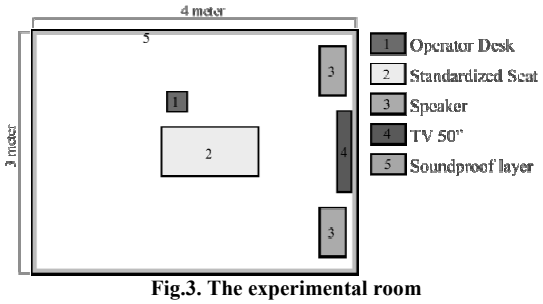


Fig.3. The experimental room

2.4. Overview of the System

The experimental method included four steps: data acquisition, pre-processing, feature selection, and classification[10]. The data acquisition step shows how the physiological signals are recorded. Pre-processing shows how the data was prepared before it was classified. Classifying the emotional state using a random forest algorithm is showed in the classification step. It is shown in Fig.4.

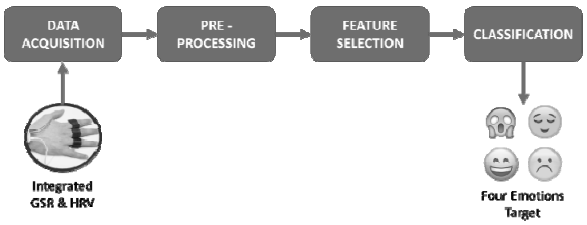


Fig.4. The Overview System

2.5. Data Acquisition

In this research, the stimulus was used by researchers to arouse an emotional state from the participants. We chose an audiovisual stimulus to arouse an emotional state from the participants by playing video packages. We chose movies that have a high effect and prepared in. All video packages are in MP4 format with a resolution of 1080 × 720 pixels and 30 frames per second. The duration of each video packages is 20 minutes that consist of four blank videos with 2 minutes duration and a four-emotions 9 (Happy, Sad, Fear, and Relaxed) videos with 3 minutes duration. Four-emotions' sequence of the emotion videos is randomly selected based on the video packages played.

We have developed a questionnaire to collect participants' opinions to got the emotional feedback of videos. After watching emotional videos, we asked the participant to scale their opinions about the videos along with valence – arousal dimensions using 9 – point scale Self Assessment Manikin (SAM) that is shown in Fig.5. Almost all researchers employed the SAM method as the tool to obtain the participants' feedback on their emotions.

Video	Duration (s)
Blank Video	120
Video Emotion 1	180
Blank Video	120
Video Emotion 2	180
Blank Video	120
Video Emotion 3	180
Blank Video	120
Video Emotion 4	180

Table 3. Stimulus Video Sequences

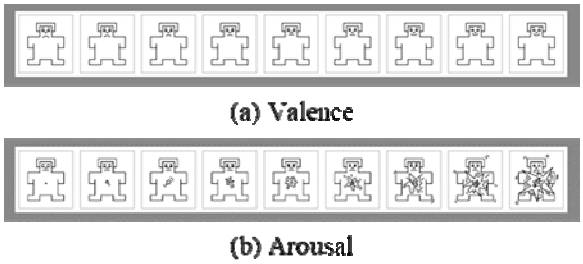


Fig.5. (a) & (b) SAM Scales to describe levels of valence and arousal[11]

2.6. Pre-Processing

Before the analysis process, the data of all participants are collected into one database. The first step, GSR, heart rate internal, and HRV per second was calculated while watching the stimulus videos. It is used regression method to get linear regression equation that shown in (1).

$$Y = Mx + B \quad (1)$$

With,

B is the baseline for each parameter

M is the parameter's change value

2.7. Feature Selection

In this step, an extra tree classifier is used to choose two parameters with the highest importance value. This selected feature would analyze using a classification method that is explained in the next step.

2.8. Classifications

A machine learning algorithm is a computer system tools to perform a task without specifically programmed instructions to estimate a result. In this work, the emotion classification tasks used the machine learning algorithm based on affective physiological signals; GSR and HRV to access the emotional state of the participants. Random forest is chosen as a classifier. It is a method based on a random decision tree and has been used widely for classification as well as regression and starts with a decision tree to find a variable-value pair from the data trained [4].

III. RESULTS AND DISCUSSION

3.1. Feature Selection

Using the extra trees classifier method with a total of 40 decision trees, it showed that the change of GSR and HRV was the most important value. The result of the extra trees classifier is shown in Table 4.

	Interval	GSR	HRV
Importance Value	0.2370	0.3388	0.4243

Table 4. The Importance Value of Interval Heart Rate, GSR, and HRV

Based on Table 4, GSR and HRV have the highest value of importance value. It is 0.3388 for GSR and0.4243 for HRV, so we chose these two parameters ad a selected feature to analyzed with the classification method, random forest. Plot data distribution of the change of GSR and HRV is shown in Fig.6 with class 1 is sad, class 2 is relaxed, class 3 is fear, and class 4 is happy.

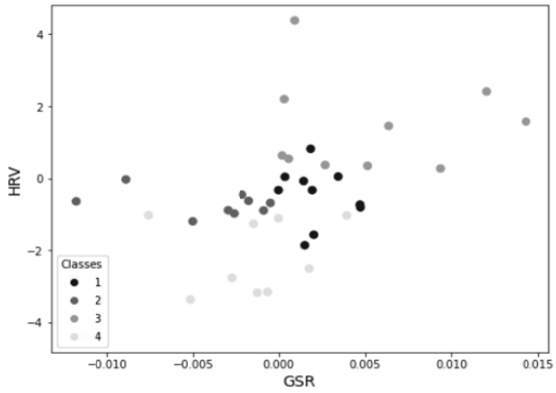


Fig.6. Plot Data Distribution

3.2. Classification

Based on the classification result using the random forest method inTable 5 shows that the total accuracy is 75%. The highest accuracy is fear emotion with an accuracy value of 91%, and the other emotions have the same value with an accuracy of 67%. This happens because fear emotion provides a significant value compared to the other emotions.

	precision	recall	f1-score	support
1	0.67	0.67	0.67	3
2	0.67	0.67	0.67	3
3	0.83	1.00	0.91	5
4	0.75	0.60	0.67	5
accuracy			0.75	16
macro avg	0.73	0.73	0.73	16
weighted avg	0.74	0.75	0.74	16

Table 5. The Classification Result

The confusion matrix of the random forest method is shown in **Error! Reference source not found.**[12].

		Predicted			
		Sad	Relaxed	Fear	Happy
Actual	Sad	2	0	1	0
	Relaxed	0	2	0	1
	Fear	0	0	5	0
	Happy	1	1	0	3

Table 6. The confusion matrix

IV. CONCLUSIONS

In conclusion, this study explored and reviewed studies that are related to quantitative emotion classification and the use of physiological signals by employing an integrated GSR and HRV signals. This study also explained that GSR and HRV signals, as well as equipment used for collecting the data acquisition, pre-processing, feature selection, and classification of these signals. The researchers used video emotions for the experimental stimuli that contained four basic emotions, such as sad, relaxed, fear, and happy. A critical discussion of this study has presented the classifier used for integrated the two bio-parameters; GSR and HRV that achieved 75% of the classification accuracy using the random forest method. Consequently, this study showed that it is possible to integrate GSR and HRV signals to be used in emotion classification to achieve high prediction accuracy using the random forest method as the classifier.

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