

# Bio-signals Collecting System for Fatigue Level Classification\*

Younggun Lee<sup>1</sup>, Yongkyun Lee<sup>2</sup> and Dongsoo Kim<sup>3</sup>

**Abstract**—Fatigue is a risk factor that reduces quality of life and work efficiency, and threatens safety in a high-risk environment. However, fatigue is not yet precisely defined and is not a quantified concept as it relies on subjective evaluation. The purpose of this study is to manage risks, improve mission efficiency, and prevent accidents through the development of machine learning and deep learning based fatigue level classifier. Acquiring true fatigue levels to train machine learning and deep learning fatigue classifier may play a fundamental role. Aims of this study are to develop a bio-signal collecting device and to establish a protocol for capturing and purifying data for extracting the true fatigue levels accurately. The bio-signal collection system gathered visual, thermal, and vocal signals at the same time for one minute. The true fatigue level of the subjects is classified through the Daily Multidimensional Fatigue Inventory and physiological indicators related to fatigue for screening the subjective factors out. The generated dataset is constructed as a DB along with the true fatigue levels and is provided to the research institutions. In conclusion, this study proposes a research method that collects bio-signals and extracts the true fatigue levels for training machine learning and deep learning based fatigue level classifier to evaluate the fatigue of healthy subjects in multi-levels.

## I. INTRODUCTION

Fatigue is a critical factor that affects not only daily life but also dangerous task, and it is very closely related to work efficiency and the risk of casualties [1-3]. However, the concept of fatigue has not been firmly established. It is reasonable to evaluate fatigue by dividing it into mental fatigue and task performance fatigue, which indicates whether a person maintains an appropriate level of physical arousal to perform a certain task. The level of fatigue is normally measured through a self-report scale or physiological signals measured through contact sensors [4-9]. Among them, the Multi-dimensional Fatigue Inventory (MFI) is known as the most reliable tool [4]. Chronic fatigue syndrome or patients requiring treatment can be diagnosed through biochemical indicators such as MFI and hormone levels [5, 6]. Cognitive fatigue is measured by EEG and muscle fatigue is measured by EMG [7-9]. However, it is not easy to predict the fatigue level in advance when fatigue becomes a risk factor among workers performing daily tasks. Some high-risk occupations,

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<sup>1</sup>Y.G. Lee is with the Department of Electronics and Communication Engineering, Republic of Korea Air Force Academy, Cheongju 28187, South Korea yglee2019 at gmail.com

<sup>2</sup>Y.K. Lee is with the Department of Mathematics, Republic of Korea Air Force Academy, Cheongju 28187, South Korea mathyouth at gmail.com

<sup>3</sup>D.S. Kim is with the Department of Physics and Chemistry, Republic of Korea Air Force Academy, Cheongju 28187, South Korea dongsookim04 at gmail.com

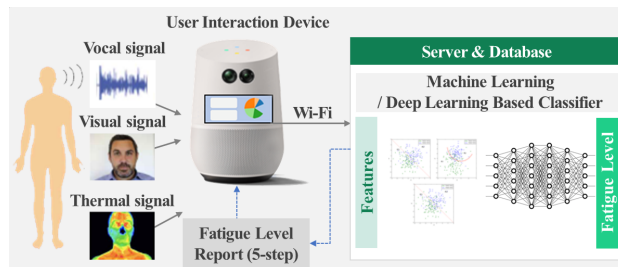


Fig. 1. System overview.

such as pilots and trailer drivers, create and use evaluation scales suitable for their occupations [10, 11]. These evaluation scales are self-report questionnaires and have limitations in subjective evaluation, and it cannot be excluded that the individual's situation intervenes in the evaluation.

We aim to develop a real-time fatigue level classifier based on artificial intelligence to overcome the limitations of subjective fatigue level evaluation. By measuring the fatigue level instantly in the field, it can prevent safety accidents and improve the quality of task performance. To develop the machine learning (ML) and deep learning (DL) fatigue level classifiers which utilize visual, thermal image, and vocal signals, the ground truth of fatigue level should be provided with training data. Thus, the process of extracting the true value of the fatigue level is the most important part. However, it has not been set up yet because certain indicators do not represent individual fatigue levels.

In this paper, the fatigue level of the subjects is classified with the proposed Daily Multidimensional Fatigue Inventory (DMFI) and four physiological indicators related to fatigue. Physiological indicators include reaction time and success rate of Psychomotor Vigilance Test (PVT) as an indicator of acute fatigue, blood lactate level as an indicator of physical fatigue, salivary C-Reactive Protein (CRP) level as an indicator of cumulative fatigue, and salivary cortisol level as an indicator of mental fatigue. In order to determine the true fatigue level, the DMFI score is first used to screen for discrepancies between subjective fatigue levels and evaluated fatigue levels. Furthermore, training data are filtered out when physiological values exceed the normal range. The main contribution of this paper is the development of a data collection system for training classifiers that can measure daily integrated fatigue in a short time via remote sensors for healthy general populations. The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board(ASMC-21-IRB-005).

## II. SYSTEM CONFIGURATION

The purpose of this study is to develop a system that can determine the level of fatigue using non-contact bio-signals as shown in Fig. 1. In the daily working environment, the user's bio-signals, optical, voice, and thermal image signals, are collected from a short distance of around 1m using a portable device. The acquired biometric data is transmitted to the main server through wireless communication, and the main server is equipped with ML and DL-based classifiers. The fatigue level analyzed in real-time is fed back to the collecting device and delivered to the user.

Since building learning data is essential for developing such a system, the data collector is proposed at first. For the convenience of data collection, we propose a device that is mobile and easy to use, and can simultaneously collect various bio-signals that can be obtained from humans to improve the reliability of data. In order to increase mobility, it is lightweight and can be operated with a built-in battery, and the collector body and cradle are designed as an assembly type to reduce the volume. In addition, a touch screen is installed to improve usability. All data in the form of optical images, thermal images, and voices are collected simultaneously to shorten the collection time of the subjects as much as possible to increase data reliability. In addition, the visual angles of optical images and thermal images are almost similar, facilitating information convergence between data. Voice can be used with mouth movements in synchronization with optical images. When the collection process is finished, the data is automatically transmitted to the server when the collector is connected to the wireless internet to back up the data.

Table 1 shows the list and specifications of hardware component items used in manufacturing to achieve the required performance. The data collection system proposed in this paper is based on Raspberry Pi 4 model B, single board computer. This is because the size is small, the price is low, and the performance is sufficient to achieve the purpose of the system while having various interfaces for connecting external hardware. Specifically, it is equipped with a quad-core 1.5GHz processor, has 8GB of RAM memory, and wireless communication is possible with two channels of Wi-Fi, 2.4GHz and 5GHz. A FLIR Lepton 3.5 is used as the thermal

TABLE I  
HARDWARE SPECIFICATIONS

Components	Specifications
Processor (Raspberry Pi 4B)	Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz, 8GB LPDDR4-3200 SDRAM 2.4GHz and 5GHz IEEE 802.11ac
Thermal Camera (Lepton 3.5)	160×120 resolution, 8.7Hz effective frame rate, -10° to +140°C (high gain mode)
Optical Camera (Pi Cam v2)	1080p 30fps, 720p 60fps video record
Microphone (Mini-USB Mic)	Condenser type, -47dB ± 4dB sensitivity, ≤ 2.2kΩ impedance
Display (7" Touchscreen)	7" 800×480 pixels, 10 finger capacitive touch
Power	Li-ion battery 2,600mAh



Fig. 2. Data collection device.

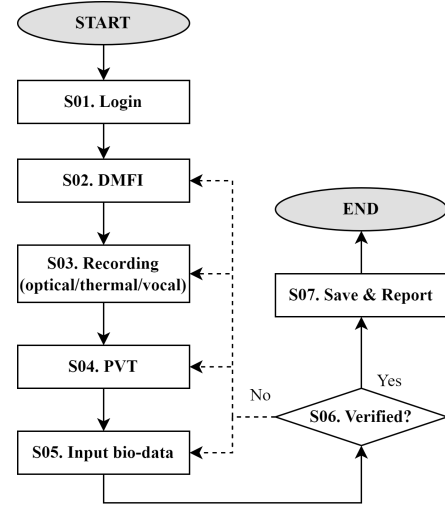


Fig. 3. Software workflow.

imaging camera, which has a thermal image resolution of 160×120 and can shoot at 8.7fps. The temperature range that can be photographed is -10° to 140°C. The optical camera used Pi Cam v2, which can shoot at up to 60fps at the resolution of 1280×720. A small USB microphone is used as the microphone. A touch screen monitor is applied for the user's data input/output. A 2,600mAh lithium-ion battery is installed as a power supply battery to increase mobility so that it can operate without power connection for more than an hour.

Fig. 2 is the completed data collection device. The body is produced by 3D printing to make the finish neat and improve the completeness. In order to minimize the size of the body, the width is adjusted to the size of the monitor, and the length is fit to the camera module installed inside the monitor. For matching the viewing angles of optical and thermal images, two cameras are placed as close as possible, and the camera is installed right above the screen for the convenience of the subject when taking images. The USB port for the microphone is placed upward, and it is possible

to attach and detach a tripod to increase mobility. When collecting data, the height of the tripod can be adjusted so that the camera shooting angle is horizontal, so even if the subjects are different, almost similar shooting angles can be made. The total weight is 819g, so it is convenient to move.

Fig. 3 shows the software workflow of the biological signal collection system. When the data collection software starts, it waits for 1) user login to distinguish the bio-signal collection target. If login is successful using the user information in the DB, 2) user responses to DMFI, 3) records video and thermal image, 4) PVT are performed, 5) inputs lactate level measured using a separate tool, 6) makes a final check on the screen where you can verify the data you have just collected at once. Finally, 7) The collection process ends with the screen where you can check the data collection progress report for the last 5 days by user in a chart, and all information is saved. The above data is classified by login ID and is effectively managed even if the data is collected from multiple collection devices at the same time and transmitted to the DB.

### III. TOOLS FOR CLASSIFYING FATIGUE LEVELS

Fatigue is divided into four categories, acute fatigue, cumulative fatigue, physical fatigue, and mental fatigue, and the DMFI includes all four categories of fatigue [12]. The overall fatigue level is calculated through the DMFI. In addition, physiological indicators corresponding to subdivided fatigue are extracted. The physiological indicator of acute fatigue is PVT, the physiological indicator of physical fatigue is blood lactate, the physiological indicator of cumulative fatigue is salivary CRP, and the physiological indicator of mental fatigue is salivary Cortisol. Although the physiological indicators representing fatigue in each category are not quantitative indicators for grading fatigue, bias in subjective evaluation can be eliminated through the reversal of subjective reports and levels of physiological indicators. Table II shows the physiological indicators associated with detailed fatigue.

#### A. Daily Multidimensional Fatigue Inventory

The multidimensional fatigue scale used as a clinical scale is a tool to measure the level of accumulated fatigue, and the risk management scale can be used as a fatigue scale that can be measured daily [13]. By fusing these two scales, we propose the DMFI that can differentiate the fatigue level even if repeated every day. The DMFI is a fatigue scale consisting of 13 questions: 2 questions for acute fatigue, 3 questions for cumulative fatigue, 3 questions for physical fatigue, 4 questions for mental fatigue, and 1 question for activity level for fatigue relaxation. Fatigue level is divided into 5 levels according to DMFI total scores and level 1 represents low-fatigue and high-arousal. When evaluated fatigue is level 1 to level 3 and physiological indicators representing subdivided fatigue are in the abnormal range, the data is classified as ND (Not Determined) and is not used for learning.

TABLE II  
TOOLS FOR CLASSIFYING FATIGUE LEVELS

Tools	Target of fatigue	Method
DMFI	Total fatigue	Questionnaire
PVT	Acute fatigue	Behavioral test
Lactate	Physical fatigue	Micro blood test
Cortisol	Mental fatigue	Immunoassay
CRP	Chronic fatigue	Immunoassay

#### B. Psychomotor Vigilance Test

PVT is one of the tools that can check an individual's level of arousal on the spot in real-time [14]. PVT is a tool for measuring the speed of response to visual stimuli. It quantifies the level of sustained attention and arousal as reaction time, as well as erroneous responses such as missing without responding or responding in the absence of stimulation. Sustained-attention and sleepiness correlated with decreased alertness, slower problem-solving speed, decreased sensorimotor function, and increased false responses to stimuli. That is, it is suitable as a tool for measuring acute fatigue related to task performance [15]. PVT has a learning effect up to the first 10 times, but if there is a reversal phenomenon between the subjective fatigue level and the reaction time thereafter, the report of the subjective fatigue level is excluded.

#### C. Blood Lactate

Lactic acid has been known as a simple fatigue substance or waste product produced as a result of lack of oxygen. However, lactic acid not only mediates between glycolysis and oxidative metabolism, but also serves as an important metabolite that adequately supplies energy during rest and exercise when energy demands increase [16]. In addition, lactic acid is a precursor of gluconeogenesis and serves as a lactate shuttle that indirectly supplies glucose to damaged tissues [17]. In the end, it is found that lactic acid functions in more than just anaerobic exercise as a source of fatigue, but lactic acid remains a major metabolite that responds to exercise stimulus accordingly. Lactic acid can be an indicator of fatigue from physical activity, and lactate in an abnormal range can be an indicator of excessive physical fatigue.

#### D. Salivary Cortisol

Cortisol is both an arousal hormone and a stress hormone, the main glucocorticoid secreted by the adrenal cortex [18]. Cortisol production has a circadian rhythm, with levels peaking about an hour after waking and falling to their lowest levels at night [19]. Levels rise independently of circadian rhythms in response to stress. Chronic stress increases the level of cortisol during the day and night, but PTSD and chronic fatigue syndrome can blunt the cortisol response even in the morning [20]. Cortisol levels at both extremes can be utilized to ensure the reliability of mental fatigue levels in subjective reports of fatigue.

### E. Salivary C - Reactive Protein

CRP is one of the acute-phase inflammatory proteins and is known as a physiological marker of the level of inflammation. CRP is primarily related to innate immunity, and levels are elevated in inflammation, tissue damage, infection, and sleep disorders [21]. CRP has diagnostic value in systemic inflammation in the body [22]. Circulating CRP levels in humans are normally very low but increase up to hundreds of folds during an acute inflammatory response. Accumulation of fatigue and lack of sleep in the absence of certain diseases can cause CRP levels to rise. If the subjective fatigue level is low but the CRP level is in the abnormal range, the subjective fatigue level data is treated as unsuitable as training data.

### IV. DB CONSTRUCTION AND APPLICATION

Data from the collector is transmitted to the DB server through wireless communication, and researchers access the DB to download and utilize the data. User information and collected data are managed by installing MariaDB 10.3 version on the collector. The fields and data types of the DB data table are summarized in Table III. In the first column, value in the parentheses indicates the data range. For example, the subjective condition value is a value between 1 and 100 points, and the subjective condition step has a value between 1 and 5 steps. The last column is an example of data for each field. There are a total of two PVT results. One is the success rate, which has a value of 0 to 1, and the response time has a value in seconds. The video and thermal image data are stored in the form of a BLOB because the subject's data must be stored for about 1 minute. In the case of video data, it is stored in the form of a TS (Transport Stream) file, and the thermal image data is stored in the form of a compressed collection file of image files with time data and minimum/maximum temperature recorded in the file name. The final fatigue level is determined on the true fatigue level classification.

About 5,000 sets have been collected so far. When creating data, the same person generates more than 40 sets of data. To prevent non-uniformity of data during NN (Neural Network) training, each person records at least 5 dataset for each fatigue level from 1 to 5. The collected data is re-evaluated

TABLE III  
DATABASE STRUCTURE

Field	Type	Example
User ID	varchar	2401
Machine ID	varchar	100000000542e564
Datetime (yymmddhhmm)	int	2208061540
Subjective condition value (1-100)	int	75
Subjective condition step (1-5)	int	2
DMFI answers (1-5) × 13	int	3
Thermal images	longblob	zip file
Video	longblob	TS file
PVT result (rate)	float	0.9
PVT response time (sec)	float	1.278
Check for bio-data (0 or 1)	int	1
Lactate value	float	7.2
Final fatigue level (1-5 or ND)	varchar	2

using the tools suggested in section III to provide a true value of fatigue and approximately 15% of them were excluded. A classifier is trained based on thermal images, optical images, and voice signals from the dataset that contains the true level of fatigue. At present, the real-time fatigue level classifier is accurate to 70% to classify fatigue into five levels. Furthermore, it shows that fatigue level classifiers get more accurate as data accumulates.

### V. CONCLUSIONS

This paper deals the technical details of establishing a data acquisition system and a true fatigue value extraction procedure to train ML/DL-based fatigue level classifier that utilizes bio-signals. Both evaluating the true fatigue levels and acquiring sufficient training data are critical to improve the performance of the fatigue level classifier. The proposed data acquisition system collects various bio-signals simultaneously. The final fatigue levels are determined by comparing and analyzing all the physiological indicators. When the subjective fatigue level reported by the subject and the fatigue level classified by the fatigue scale score do not match, those data are excluded from the training. Therefore, the proposed procedure minimizes subjective bias in subjective fatigue evaluations through increased reliability and accuracy at determining the universal true fatigue level.

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