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Development of a Web Platform System for Worker Protection using EEG Emotion Classification

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뇌파 기반 감정 분류를 활용한 작업자 보호를 위한 웹 플랫폼 시스템 개발

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Abstract As a primary technology of Industry 4.0, human-robot collaboration (HRC) requires additional measures to ensure worker safety. Previous studies on avoiding collisions between collaborative robots and workers mainly detect collisions based on sensors and cameras attached to the robot. This method requires complex algorithms to continuously track robots, people, and objects and has the disadvantage of not being able to respond quickly to changes in the work environment. The present study was conducted to implement a web-based platform that manages collaborative robots by recognizing the emotions of workers - specifically their perception of danger - in the collaborative process. To this end, we developed a web-based application that collects and stores emotion-related brain waves via a wearable device; a deep-learning model that extracts and classifies the characteristics of neutral, positive, and negative emotions; and an Internet-of-things (IoT) interface program that controls motor operation according to classified emotions. We conducted a comparative analysis of our system's performance using a public open dataset and a dataset collected through actual measurement, achieving validation accuracies of 96.8% and 70.7%, respectively.

Key Words : Brain-Computer Interface (BCI), Electroencephalography (EEG), Emotion classification, Deep learning, IoT; Web platform system

요 약 인터스트리4.0의 주요 기술인 인간-로봇 협업은 작업자의 안전을 보장하기 위한 추가적인 조치들이 필요하다. 협동로봇과 작업자간 충돌을 회피하는 기존 방식은 주로 로봇에 부착된 센서와 카메라를 기반으로 총돌을 탐지한다. 이러한 방식은 로봇, 사람 물체를 지속적으로 추적하고 충돌회피를 위한 복잡한 알고리즘이 필요하며, 작업 환경 변화에 빠르게 대응하지 못하는 단점이 있다. 본 논문은 인간과 로봇이 협업하는 과정에서 작업자가 위험을 느낄 때의 감정을 인식하여 협동로봇과의 충돌을 방지할 수 있는 웹 기반 플랫폼을 개발하였다. 이를 위해 웨어러블 뇌파장치를 이용하여 감정 관련 뇌파를 수집하고 저장하는 웹 기반 애플리케이션을 개발하였으며, 중립/긍정/부정 감정의 특징을 추출하고 분류하는 딥러닝 모델을 제안하였다. 또한 분류된 감정에 따라 모터동작을 제어하는 사물인터넷 인터페이스 프로그램을 개발하였다. 구현된 시스템의 성능분석을 위해 공개 데이터세트와 실제 수집된 데이터 세트를 사용하여 제안한 딥러닝 모델의 성능을 분석하였다. 공개 데이터 세트의 경우 정확도는 96.8%이며, 실제 수집 데이터세트의 경우 정확도는 70.7%이다.

주제어 : 뇌-컴퓨터 인터페이스, 뇌파, 감정분류, 딥러닝, 웹기반시스템

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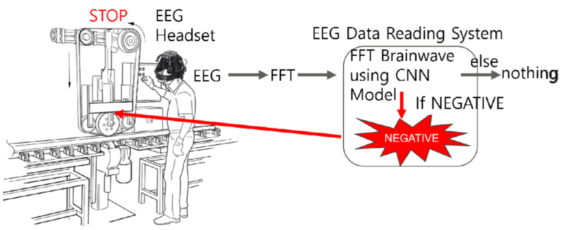
1. Introduction

With the introduction of smart factory technology in the industrial field, efficient ICT-grafted manufacturing technologies have become increasingly important, and next-generation industrial and collaborative robots grafted with ICT technology are expected to lead the future manufacturing market [1]. Human-robot collaboration (HRC) represents a key technology of the Fourth Industrial Revolution. Collaborative robots, which cooperate with human workers to increase work efficiency, are rapidly replacing conventional industrial robots, changing the manufacturing environment. This approach is cheaper than conventional industrial robotics as it enables partial automation. Consequently, many companies have recently adopted this approach. In particular, Korea ranks first in the world in terms of robot density with 85 industrial robot units per 10,000 employees. Korea's industrial structure is advantageous for partial automation, as the automotive and electronics industries are major demand sources for robotic collaboration [2]. The deployment of collaborative robots requires an industrial environment wherein robots and humans share a workspace and cooperate with each other. To maintain such as environment, it is paramount to ensure safe interactions between the robots and human workers. In 2016, the ISO/TS 15066 standard – entitled 'Robots and Robotic Devices – Collaborative Robots' – was established as an extension of ISO 10218 specifically aimed at collaborative robots [3]. According to ISO/TS 15066, collaborative robots must operate as conventional industrial robots so long as no personnel are present inside the work area. However, ceasing operations whenever a human enters the work area may lower factory productivity. Research on robot control based on smart situational awareness using AI is being actively conducted to mitigate this issue. Because brain waves vary with respect to a person's thoughts and emotions, they can be used to approximate the mental states and intentions of personnel. Peripheral device control using brain waves may serve as a useful human-machine interface (HMI) technology when quick response is required, as it allows users to mentally control devices. Because the latest electroencephalographic (EEG) devices are wearable, they are convenient to deploy from the perspective of user-friendliness. Furthermore, brain-computer interface (BCI) technology is considered the ideal HMI technology, as it requires no additional physical stimulation for control. However, BCI has not yet reached the commercialization stage owing to a lack of necessary base technology. Existing protocols in the HRC field monitor the positions and behaviors of workers using sensors such as cameras, laser sensors, and inertial measurement units (IMUs), or avoid collisions in advance by recognizing them via safety barriers placed around robots. However, few attempts have been made to avoid collisions with collaborative robots by recognizing the emotions of personnel. Fig 1 illustrates the concept of collision avoidance based on EEG emotion recognition. In this study, we developed a web-based system that controls robotic operations by recognizing the workers' emotions, particularly when workers feel a sense of danger in the collaborative process. The developed system collects brain waves from users. After extracting and classifying the collected EEG features using the proposed deep learning model, these features are used for motor control in the robots.

The rest of the paper is structed as follows. Section 2 provides an overview of prior collision avoidance studies in the HRC field, as well as studies pertaining to emotion classification in the BCI field. Section 3 describes the system configuration and major components of the developed system. Section 4 presents a performance evaluation of the proposed deep learning model. Finally, Section 5 concludes the study and presents potential future directions of research.



[Fig. 1] Concept of collision avoidance based on EEG emotion recognition

2. Literature Review

2.1 Collision Avoidance

A primary concern in the implementation of industrial HRC is human-robot collaborative safety. Physical contact between robots and personnel may be transient or quasi-static. Transient contact refers situations wherein a part of the human body is momentarily shocked, but not clamped or pinched, by a robot, whereas quasi-static contact refers to situations wherein a part of the human body is clamped by or caught in a moving part of a robot. In cases of quasi-static contact, force and pressure must be continuously applied to the body until the robot system is normalized, making it a contact state with a high risk of human injury [4]. Preventing human-robot collisions through pre-collision control prior to physical contact may effectively ensure user safety. The underlying concept of collision avoidance is to ensure worker safety by preventing hazardous contact in advance using preventive methods and systems. Safeea uses various sensors to capture the human operator's position and motion, and adapts the manipulator's path based on a framework that incorporates artificial potential fields [5]. Chen designed a real-time motion planning and control system of a robotic arm to ensure human-robot collaborative safety [6]. This system utilizes depth images from multiple KinectV2 cameras to track people and objects within the robot workspace. Landi designed an optimization-based algorithm that ensures obstacle avoidance while minimizing the difference between the nominal and commanded acceleration inputs [7].

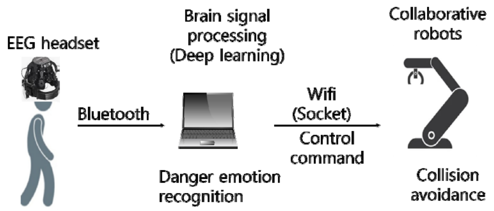
2.2 Emotion Recognition

Deep-learning technology is used in fields including autonomous driving, aerospace, medical research, and industrial automation. In particular, convolutional neural networks (CNNs) have achieved success in many difficult image classification problems. Studies deploying deep-learning models for EEG-based emotion recognition are currently in progress, with CNNs, long short-term memory (LSTM), and hybrid models having been proposed for the task [8,9]. Using a GoogleNet-inspired CNN model, Gao incorporated Hjorth, differential entropy, and sample entropy in the time domain, as well as power spectral density in the frequency domain, as factors for feature extraction. The proposed model achieved accuracy measures of 80.02% and 75.22% for arousal and valence, respectively [10]. Hasan proposed a deep-learning technique that classifies 64 complex emotions using a one-dimensional CNN, with FFT used to extract features, achieving accuracy measures of 96.63% and 96.18% in two-class classification, and 93.83% and 93.79% in eight-class classification, for valence and arousal, respectively [11]. Alhalaseh used four classification methods – naïve Bayes, KNN, decision tree (DT), and CNN – to classify emotional states. Using the Higuchi's fractal dimension (HFD) and entropy as feature extraction techniques, an accuracy of 95.20% was achieved [12]. Yin proposed a deep-learning model that combines a graph convolutional neural network (GCNN) and LSTM, with differential entropy used for feature extraction. The proposed model achieved accuracy measures of 90.45% and 90.60% for valence and arousal, respectively [13].

3. Materials and Methods

3.1 System Structure

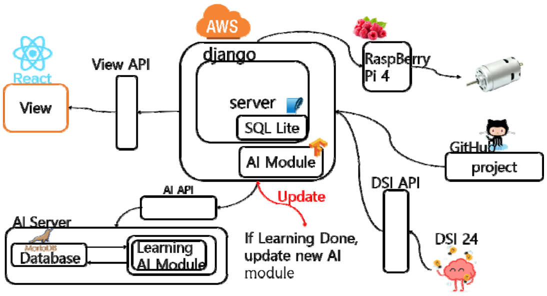
We designed a web-based EEG emotion recognition system that recognizes workers' emotions when they feel danger. The proposed system ensures worker safety by controlling the operations of peripheral devices according to the detected emotions. Brain signals pertaining to the emotions of personnel are transmitted to the server via EEG headset. The server, which is responsible for brain signal processing, extracts and classifies the received brain signals using deep learning. The classified signals are then converted into motor control commands and transmitted to the Raspberry Pi. These commands either start or stop the direct current (DC) motor connected to the hardware board through the general-purpose input/output (GPIO) pin control. As shown in Fig. 2, the system is divided into three primary components. The first component, a web platform that includes a user interface to measure brain signals, performs control tasks assigned to the web server. The second component extracts features from the collected brain waves and classifies emotions using deep learning. The third component is an IoT interface that controls the DC motor connected to the Raspberry Pi.



[Fig. 2] Structure of EEG-based emotion recognition system

3.2 Web-based Emotion Recognition Platform

The web-based emotion recognition platform detects emotional brainwaves derived from users, classifies emotions using AI modules, and controls robotic operations according to the classified emotions via wireless communication. The developed system primarily comprises a user interface, Django web server framework, an AI server that extracts and classifies emotional features, and an IoT module that controls robotic operations. Fig. 3 illustrates the structure of the web-based emotion recognition platform. The user interface performs user login and emotion induction functions, with the latter performed using test media. When test media are presented, a corresponding emotion classification result is displayed. When the measurement button is pressed, positive, negative, and neutral images for emotion induction appear in the testing media area, and the EEG signals during measurement are displayed in the EEG data graph area. We chose AWS, a platform that can guarantee our needs. Because AWS has ELB(Elastic Load Balancer), which can support load balancing, and since it is a cloud server, it has much faster computing power than local. Furthermore, we have embeded AI module in our Web-server. AI module uses Python TensorFlow. As a result, we chose Django as a reliable Pyton Web-Framework, which keeps updating for a long time.



[Fig. 3] Structure of web-based emotion recognition platform

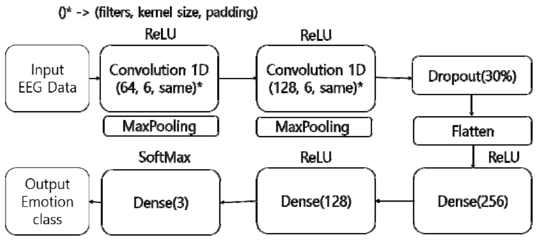
3.3 EEG Data Acquisition

We conducted an experiment with four adult male participants in their twenties, with an average age of 25.1 years (range: 23-28), none of whom had a history of psychiatric or neurological disorders. Participants were instructed not to consume alcohol or caffeine within a day prior to the experiment, as well as requested sufficient sleep during that period. Prior to the experiment, all participants listened to an explanation of the experimental method and relevant precautions, as well as signed a consent form.

The collection of emotion-related EEG data requires stimuli capable of inducing emotions. For this purpose, we deployed IAPS images [14]. Images to induce neutral, positive, and negative emotions were selected based on arousal and valence as described in the IAPS technical manual. The experiment was conducted in a quiet laboratory. Participants in the experiment were asked to wear headphones, sit on a chair, stare at the monitor in front of them, and minimize their body and neck movements while viewing the images. First, a 2-second black screen appears. This screen indicates that the experiment is starting. A cross mark will then appear for 4 seconds. The cross is meant to induce neutral emotions. Subsequently, an information message screen indicating that an image will be displayed for 2 seconds appears, followed by a negative image or a positive image for 2 seconds. Thereafter, a cross mark for 4 seconds, a guide message for 2 seconds, and an image for 2 seconds are repeated a total of 20 times. The 2 second black screen that appears at the very end of the trial means the end of the trial. 1 trial consists of 20 images and takes about 3 minutes. Furthermore, we used a Wearable Sensing DSI-24 EEG sensor and a DSI-streamer software to collect EEG. The DSI-24 is a non-invasive wearable EEG device primarily used in studies pertaining to brain function. It measures EEG in a simple and user-friendly manner, and transmits the measured data to a PC via Bluetooth or a wired micro USB cable. The DSI-24 headset contains 20 active and two reference electrodes positioned according to the international 10-20 system. The DSI-streamer software performs high- and low-pass filtering on the collected EEG data, and displays said data on the screen in real time. Raw EEG data are saved in the .EDF or .CSV format. In this study, data were collected from the eight locations corresponding to the prefrontal cortex and frontal lobe, which are known to be closely linked to emotions: Fp1, Fp2, F3, F4, F7, F8 [15].

3.4 Proposed Deep Learning Model

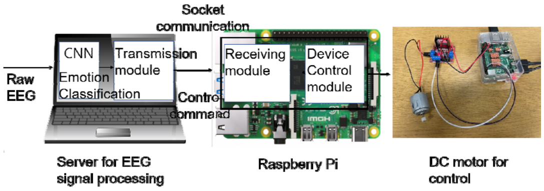
The deep-learning model used in this study was designed to extract and classify relevant EEG features as quickly as possible when a worker feels in danger. Such a model must classify emotions in real-time using only EEG signals. Accordingly, we designed the lightweight CNN model depicted in Fig. 4, which accepts raw EEG data received from the EEG headset as input. The model's batch size, number of epochs, and dropout ratio were set to 10, 20 and 30%, respectively. The CNN architecture consists of two convolutional layers, two max pooling layers and three fully connected layers. Accepting 600 raw EEG data of six positions for two seconds as input, the model outputs 0 (neutral emotion), 1 (positive emotion), or 2 (negative emotion). We developed the model using Anaconda 5.2, Python 3.6, TensorFlow 1.5, Numpy 1.6, and Keras 2.2.4.



[Fig. 4] Structure of proposed CNN model

3.5 IoT Interface for Motor Control

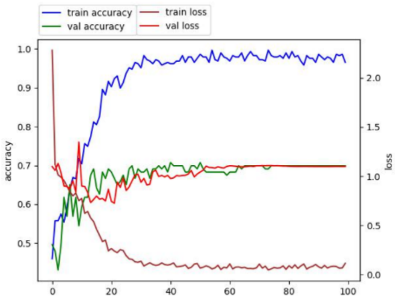
The IoT interface module receives emotion classification results from the deep-learning model as control commands. If a negative emotion is received, the module terminates robotic operations. Wi-Fi socket communication is performed between the server and Raspberry Pi. As shown in Fig. 5, the IoT interface comprises three functional components. The first component is a transmission module that receives emotion classification output from the CNN and transmits it to the Raspberry Pi via receiving module. Specifically, the transmission module transmits the ternary classification results to the receiving module via socket communication, and the receiving module only transfers the received value to the second component, namely the device control module. This module starts or stops the motor according to the control command received by the Raspberry Pi. The third component is a hardware circuit designed to start or stop the motor. If the received value is 0 or 1, the DC motor continues to operate; if the received value is 2, the motor terminates. All aforementioned modules are implemented in Python.



[Fig. 5] Process of IoT interface for DC motor control

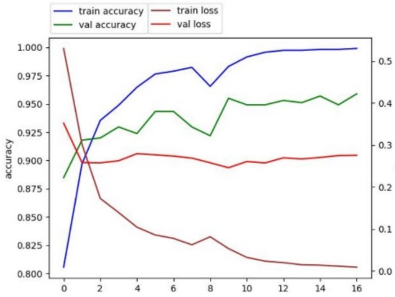
4. Results and Discussion

The most important measures of the overall system's performance are the accuracy and execution time of emotion classification. We used loss and accuracy as verification measures for the deep-learning model. Because loss represents the error associated with the output, it must be minimized, whereas accuracy must be maximized. Fig. 6 presents the performance of the proposed CNN model using the collected data, with a validation accuracy of approximately 70.7%. In the case of training data, the loss was 0.1025 and the accuracy was 0.9617, in the case of validation data, the loss was 0.9764 and the accuracy was 0.7073.



[Fig. 6] Classification performance of proposed CNN model using our dataset

The performance of deep-learning models is closely related to the amount and quality of training data. We analyzed the proposed model's performance using an existing public data set, namely the EEG Brainwave Dataset: Feeling Emotions, obtained from Kaggle. The EEG data were measured over three minutes for each emotion (positive, neutral, negative) for two people (1 male, 1 female) using the Muse EEG device, with video media used to induce emotions. Data were split between training, testing, and validation sets according to a ratio of 5.6:2.4:2. The proposed CNN model achieved a test accuracy of approximately 96.8%. In the case of training data, the loss was 0.0114 and the accuracy was 0.9992, in the case of validation data, the loss was 0.2382 and the accuracy was 0.9688, in the case of test data, the loss was 0.1462 and the accuracy was 0.9625. Fig. 7 shows the performance of the proposed CNN model using the Feeling Emotions dataset. From the results displayed in Figs. 6 and 7, we can conclude the following: firstly, the proposed CNN model achieves an accuracy exceeding 70% despite using raw EEG signals as input data; secondly, higher performance can be expected if sufficient data are secured through accurate measurement.



[Fig. 7] Classification performance of proposed CNN model using feeling emotions dataset

5. Conclusion

In this study, we developed a web-based emotion recognition system using a wearable EEG device. Our objective was to protect workers by recognizing their sense of danger when collaborating with robots in industrial settings and accordingly controlling the robotic operations. To this end, we developed a web-based emotion recognition platform that collects and processes the emotional brainwaves of users via wearable EEG device, and deploys a CNN model to extract features from the collected brainwaves and classify emotions. In addition, we developed a Raspberry Pi-based control program that controls robotic functions according to the detected emotions. Classified emotions are delivered to the IoT module as commands via Wi-Fi socket communication. To evaluate system performance, we used actual measurements along with a public dataset, achieving accuracy measures of 70.7% and 96.8%, respectively. The developed system uses raw EEG data measured over two seconds as input, which opens the possibility of real-time emotion recognition. In addition, the performance difference of more than 20% for the two datasets closely relates to the characteristics of the input data. Further research is needed to reduce overall system response time to achieve real-time applicability and increase classification accuracy.

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