A concept for emotion recognition systems for children with profound intellectual and multiple disabilities based on artificial intelligence using physiological and motion signals

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Abstract

Purpose: This study proposes a concept for emotion recognition systems for children with profound intellectual and multiple disabilities (PIMD) based on artificial intelligence (AI) using physiological and motion signals.

Methods: First, the heartbeat interval (R–R interval, RRI) of a child with PIMD was measured, and the correlation between the RRI and emotion was briefly tested in a preliminary experiment. Then, a concept based on AI for emotion recognition systems for children with PIMD was created using physiological and motion signals, and an emotion recognition system based on the proposed concept was developed using a random forest classifier taking as inputs the RRI, eye gaze, and other data acquired using low physical burden sensors. Subsequently, the developed emotion recognition system was evaluated, validating the proposed concept. Finally, we proposed a validated concept for emotion recognition systems.

Results: A correlation was found between the RRI and emotion. The emotion recognition system was created based on the proposed concept and tested. According to the results, the recognition rate of “negative” and “not negative” of 70.4% ± 6.1% (Mean ± S.D.) of the developed emotion recognition system was

higher than 48.5% ± 5.0% of an unfamiliar person used as a control.
Conclusion: The results indicate that the proposed concept for the emotion recognition systems is useful for communicating with children with PIMD.

Keywords: children with profound intellectual and multiple disabilities; emotion recognition; heartbeat interval; artificial intelligence; physiological signal; motion signal; communication assist system

Implications for rehabilitation

- A new concept based on artificial intelligence for emotion recognition systems for children with profound intellectual and multiple disabilities (PIMD) using physiological and motion signals is proposed.
- An emotion recognition system based on the proposed concept developed using a random forest classifier taking as inputs the heartbeat interval, eye gaze, and other data acquired using low physical burden sensors was tested in terms of the emotion recognition rate.
- The recognition rate of "negative" and "not negative" of the developed system (i.e., 70.4% ± 6.1%) is higher than that of an unfamiliar person (i.e., 48.5% ± 5.0%).
- The proposed concept for emotion recognition systems may be useful for communicating with children with PIMD.

Introduction

Profound intellectual and multiple disabilities (PIMD) is characterized by an individual who is diagnosed with a low intelligence quotient and more than one disability [1]. In

Japan, children aged 15 years old or below who have 25 points or higher on the "score of children with PIMD" and maintain the score for 6 months or longer are diagnosed with PIMD [2]. Children with PIMD exhibit poor emotion expression, which is the process of sending out information about one's emotional state, including emotion signals in facial expressions, voice tone, and speech rate [3–6]. This condition makes emotion recognition and nonverbal emotional communication difficult. Emotion recognition is defined as the accurate recognition, decoding, or perception of received nonverbal emotional information [4,7]. Emotion expression and recognition are a pathway of nonverbal emotional communication [7].

A questionnaire study revealed that it is difficult for teachers to find movements as the emotion expression of all the movements of children with PIMD and recognize their emotional information because their face, eye, head, hand, arm, and leg movements and those of their other body parts can be extremely weak or at times absent [8]. This difficulty brings embarrassment to teachers in terms of the way they teach children with PIMD [9,10]. However, these movements can be clues for recognizing their emotional information, communicating with them, and teaching them. For example, the reciprocation and the stopping time of the eye movements of a child with PIMD differ according to the situation (e.g., medical treatment and daily life support) [11].

Accordingly, conventional studies on assistive devices used in children with PIMD, which utilized motion signals, were conducted. One study developed a system that detects motion every second in a tablet placed in front of the face based on the changes in the pixel values around the mouth and the eyes and alerts the user with a buzzer [12]. For other assistive devices, another study developed a system for recognizing a user's intention through eye gaze [13], brain signals in the motor cortex [14], voice signals [15], and tongue motion [16]. However, recognizing the user's emotion only by capturing the body motion is impossible, and it is only a subjective judgment of the emotion by others.

Both motion and physiological signals are studied to understand the emotions of children with PIMD. A heartbeat has the advantages of easy measurement compared to other physiological signals and low physical burden for children with PIMD [17]. It may be helpful for emotion recognition because some emotions of able-bodied individuals are related to the heart rate variability under certain conditions [18–20]. In a study focusing on the response of two children with PIMD to a verbal stimulation, one child exhibited a heartbeat response without a body movement response, while the other did not show both responses; instead, the child exhibited a mouth movement response to another smell stimulation [21]. Considering that the body movements of children with PIMD are extremely weak, and their motion and physiological signals depend on individuals, models using the data acquired from sensors for emotion recognition have been proposed only for able-bodied people [22,23]. The characteristics of the physiological signals of children with cerebral palsy, many of whom are judged as having PIMD, are different from those of able-bodied people [24]. An emotion recognition system should be tailored to each individual because the condition of each child with PIMD is unique, as is the part of the body that can be moved.

Artificial intelligence (AI) is defined as the science and engineering of making intelligent machines, especially intelligent computer programs [25]. In recent years, AI has been rapidly developed [26], exhibiting the potential to recognize the emotions of children with PIMD from motion and physiological signals (e.g., heartbeat) through its high classification performance. AI can also solve the dependency of the relationship of motion and physiological signals to their emotions on each individual by its learning ability.

In this study, we create a concept based on AI for emotion recognition systems for children with PIMD using physiological and motion signals, develop and test an emotion recognition system based on the proposed concept, and propose a validated concept. The proposal of this concept is novel and significant as the first step of the future works on the emotion recognition for and the nonverbal emotional communication with children with PIMD because, to the best of our knowledge, no previous study has described the feasible emotion recognition systems for them.

Methods

As part of an early-stage proposal of a concept for emotion recognition using physiological and motion signals, we developed herein an emotion recognition system prototype based on the proposed concept and tested this system to validate the concept using one participant. The procedure for the proposed concept comprised three parts:
1) Preliminary experiment to explore the relationship between heartbeat and emotion;
2) Creating a concept and developing a prototype system for emotion recognition;
3) Testing the developed system and proposing a validated concept for emotion recognition.

Preliminary experiment to explore the relationship between heartbeat and emotion

The physiological and motion signals of one participant were measured during outpatient physical therapy, which the participant had been regularly receiving from one of this paper's authors, CK, once or twice a month for eight years and eleven months when invited to participate in the study (Figure 1). Two of this paper's authors, CK and HS, distributed flyers and introduced the study to the parents of children with PIMD. The children included in this study met the following criteria: (1) Communication

Function Classification System (CFCS) levels IV–V [27]; (2) with ages above 5 years and 0 months; (3) Gross Motor Function Classification System (GMFCS) levels IV–V [28,29]. The participant is a 10 year-old boy who has cerebral palsy with profound intellectual disability and epilepsy. He is bedridden and classified as a level five on the GMFCS. He also wears a tracheal cannula to aspirate the sputum frequently. No voluntary movements were observed, except for occasional tongue movements, which also appeared to be involuntary. He seemed unable to communicate his emotion verbally and through facial expressions, but his parent sometimes identified his emotions (e.g., "He likes it." or "He was stressed.").

The participant was observed as changing emotion during the therapy. This therapy primarily consisted of his practice of the motion range of the joints in the supine position and occasionally in the seated position through the help of the physical therapist and was under the observation of his parent. His electrocardiogram (ECG) and acceleration in the chest and electromyogram (EMG) and acceleration on the right digitorum and emoris were measured using paste-type wearable sensors (BioStamp, MC10) with 1000 Hz ECG and EMG sampling frequencies and 31.25 Hz acceleration. His therapy scene, eye gaze, and facial expression were recorded using three video cameras with 30 or 60 fps. A session consisted of a set of therapy for 40 min and three sessions were conducted on separate days in one year in this study. Each signal was measured and tested in one session of them to determine whether or not it would correlate with the final emotion label expressing the estimated emotion, which will be described below.

The study protocol was approved by the Research Ethics Committee of Kitasato University School of Allied Health Sciences (2020-012, 19 June 2020). Before testing, the child's parent was informed about the procedure and the purpose of the study and signed an informed consent form.

Creating a concept and developing a prototype system for emotion recognition

A concept for emotion recognition

We created a concept for emotion recognition, in which AI recognizes the emotions of children with PIMD using physiological and motion signals. We hypothesized that physiological signals, especially a heartbeat, would show a correlation with the emotion of children with PIMD and aimed to validate it using the abovementioned procedure. For the emotion recognition, we focused on the participant's motion signals (e.g., eye and tongue motions) and the EMG in his muscles that are weakly movable because motion is important in emotion recognition [12]. Emotions could be recognized using physiological and motion signals, but the correlation between emotion and physiological and motion signals would be extremely complicated. AI recently showed significant advances in categorizing a set of data into classes and may be able to solve the abovementioned complexity.

Physiological and motion signals for emotion recognition systems

Based on the proposed concept for emotion recognition systems based on AI using the physiological and motion signals, we developed an emotion recognition system prototype that can be used in real time with a personal computer, a tablet, or a smartphone to realize smooth communication with both familiar and unfamiliar people. Eighteen types of signals, including eye gaze, tongue motion, EMG, and heartbeat interval, R–R interval (RRI), which is the time elapsed between two successive R–waves on ECG, were used as the physiological and motion signals featuring emotion (Table 1). These signals were measured using low physical burden sensors, such as wearable sensors and video cameras, during the participant's outpatient physical therapy, as described above.

As a physiological signal, the RRI was obtained from the ECG signals [30], and general features (e.g., mean and median) were used every 10 s. The slope *a*, intercept *b*, and coefficient of determination R^2 in the linear approximation of the RRI time series for 10 s was used to consider the temporal change in the RRI.

Certain frequency bands of the heart rate variability tend to correlate with a certain nervous system activity. Note that the correlation for children with cerebral palsy is not the same as that for able-bodied children [24]. We used low-frequency power (LF) and high-frequency power (HF), which are frequency activities standardized in 0.04–0.15 and 0.15–0.40 Hz frequencies, respectively, and the LF/HF ratio [30,31]. Although the HF range for pediatric participants who breathe faster than adults should be appropriately adjusted [24], the peak of the participant's spectrum was confirmed to exist in the standard HF range of 0.15–0.40 Hz, and no adjustment was needed.

The eye gaze, tongue motion, breathing, and EMG were expressed in numerical form and used as the motion signals because of their importance. The eye gaze was expressed as 1 and 0 in the upward and downward directions, respectively. The tongue motion was expressed as 1 and 0 in motion and no motion, respectively. Breathing was expressed as 1 when taking a deep breath and 0, otherwise. The integral of the EMG (iEMG) is an indicator of the muscle activity intensity; hence, the iEMG on the right digitorum and the right femoris of the participant for 10 s was used [32].

Random forest classifier based on AI for the emotion recognition system

A random forest (RF), which is an ensemble learning method for classification using many decision trees, was employed to classify the acquired physiological and motion signal data into a certain emotion through AI [33]. The RF algorithm would be suitable for the emotion recognition systems for children with PIMD because it requires less data for learning and is more explainable than other algorithms (e.g., artificial neural networks (deep learning)). In this work, the RF classifier was implemented in the emotion recognition system using Scikit-learn, which is a Python machine learning library [34].

To learn the system and tailor it to the participant, the RF requires a dataset of paired inputs and labeled outputs that correspond to the physiological and motion signals and emotion labels for each emotion, respectively. However, recognizing the emotions of children with PIMD on site and in real time is extremely difficult; hence, emotion labels cannot be obtained in general ways. Emotion labeling in the learning process that does not require a real time process differing from the test process of the system is, therefore, important. Furthermore, a reliable emotion labeling procedure is required.

The desires to act during the outpatient physical therapy were labeled as "again" for the participant wanting to do it again, "not again" for the participant not wanting to do it again, "neutral" for neither of the two, and "unknown" for being unable to judge it [35]. Judging the negative emotion of the participant is relatively easy and reliable, and the RRI is related to a negative emotion rather than positive and neutral emotions for able-bodied people [36]. Thus, "not again" was converted into the emotion label of "negative" expressed by −1; "again" and "neutral" were converted into "not negative" expressed by 1; and "unknown" was expressed by 0. This simplified the emotion labels to a one-dimensional value of −1, 0, or 1.

An estimator, who was likely to provide reliable emotion labels, created the emotion labels. The estimator may have perceived the created emotion as confident in one scene, but not in another. Therefore, the confident indices included "not confident," “little confident,” “pretty confident,” and “confident” expressed numerically as 1, 2, 3, and 4, respectively. Multiplying an emotion label value by a confident index yielded an emotion label value with confidence.

For more reliable labels, emotion labels with confidence were created by three estimators, namely a physical therapist who regularly treats the participant and two co-authors of this study, including a physical therapist, who repeatedly watched videos and were blinded to the results from the other data (e.g., RRI, ECG, and EMG). The sum of the emotion labels estimated by the three estimators every 10 s was calculated in the range from −12 to 12 to increase the reliability like ensemble prediction [37]. By trial and error, the final emotion label was obtained by setting the threshold value to 3 (25% of the maximum value of 12 in three persons) and estimating the summed value of 3 or more as “not negative,” that of −3 or less as “negative,” and the other value as “unknown.” The usage of the values by the three estimators has the following advantage; the summed value is high if one of the estimators has confidence in the emotion labels, resulting in reliable final estimation labels.

Figure 2 presents an overview of the developed emotion recognition system.

Testing the developed system and validating the concept for the emotion recognition systems

We tested the developed emotion recognition system by comparing its recognition rate with that of an unfamiliar person in the same experiment as in the preliminary experiment. The unfamiliar person was selected under the condition that he did not have much knowledge of the participant and had no particular expertise in emotion recognition considering the need of assistive devices in emotion recognition in actual cases. As well as estimators, he created the final emotion labels using the threshold value of 1 (25% of the maximum value of 4 in one person), which was obtained as the best effort by trial and error, every 10 s by watching the video in the timeline.

The concept for the emotion recognition systems was validated by using the F-measure, a measure frequently used for imbalanced data [31], as an evaluation metric to measure the system recognition rate considering the imbalance in the final obtained data (i.e., "unknown" did not indicate any emotion in the system, making it not much meaningful, and the average of the F-measure values of "negative" and "not negative" was used as the system recognition rate).

Analyses

The recognition rates of the emotion recognition system and the unfamiliar person were obtained through a four-fold cross-validation and statistically analyzed. In the four-fold cross-validation, the data were randomly divided into four folds of approximately equal size [38]. The first fold was treated as a validation set. The learning for the RF classifier was fit on the three remaining folds. This procedure was repeated for four times, and each time, a different fold of the data was treated as a validation set. The results were expressed as mean ± S.D. t-Test was performed to determine the statistical significances of the differences. p-Values less than 0.05 were considered significant.

Results

Preliminary experiment to explore the relationship between heartbeat and emotion

The RRI was obtained from the ECG. The median of the RRI was selected as a representative value of the state every 10 s (Figure 3). A significantly decrease in the median of the RRI synchronized with the estimators' judgment from the video that the participant may have a "negative" emotion.

Testing the developed emotion recognition system

Figure 4 depicts the time series of the emotion label value with confidence estimated by each estimator, summed emotion label value of the three estimators, and final emotion label value. Figure 5 compares the time series of the emotion label value with confidence estimated by the unfamiliar person and the final emotion label value.

The system recognition rate was obtained as the F-measure average of "negative" and "not negative" through the four-fold cross-validation. The system recognition rates of "negative" and "not negative" (i.e., 70.4% ± 6.1% (mean ± S.D.)) were significantly higher than those of the unfamiliar person (i.e., 48.5% ± 5.0% ($p < 0.05$)) (Table 2).

Discussion

Potential of emotion recognition using physiological and motion signals

In the preliminary experiment, the participant seemed "negative" from the video when the median of the RRI decreased. In some of the "negative" scenes, muscle stretching was performed, and the participant appeared to be in pain. The time series of the median of the RRI shown in Figure 3 partially agreed with those of the summed emotion label value of the three estimators in Figure 4(d), especially in the low RRI median range. A conventional study found that pain changes the heart rate [39]. Hence, the RRI may be related to the emotions of children with PIMD and beneficial for emotion recognition. By contrast, when the median of the RRI decreased in another scene, the participant's posture was changed from a supine position to a sitting position. The autonomic nervous activity changed with the changing posture [40]. The result in this study was consistent with it, indicating that the RRI may change because of both emotion and posture changes, and no simple one-to-one correspondence exists between the median of the RRI and emotion. Meanwhile, the parent believed that it was negative when the participant's eyes raised, and that it was a response from the participant when the tongue moved. Recognizing emotions by AI requires the use of not only the RRI, but also of other physiological and motion signals, such as eye gaze and tongue motion.

Validity of the proposed concept and usefulness of the developed system

The emotion recognition system based on our proposed concept, which uses the RF classifier as AI taking physiological and motion signals as the inputs, recognized the "negative" and "not negative" emotions of children with PIMD by 70.4% significantly higher recognition rate compared to the unfamiliar person, who had 48.5%. The finding suggests that the proposed concept may be valid. This also implies that the emotion recognition system based on the proposed concept can be useful as a real time assistive system that will enable children with PIMD to communicate with others, improve their quality of life, and allow their caregivers to more easily care for them. Although no practical communication assistive system has yet been made available for emotion recognition for children with PIMD, many gaze-based assistive systems have been used as conventional ones for nonverbal children with severe physical impairments. One study on children with severe physical impairments indicated that gaze-based assistive systems provide an opportunity for people involved with these children. These systems allow them to better understand the children's needs, including the "not again." This is a relief because parents need not worry much about others not being able to understand their children's needs [41]. Although children with PIMD cannot use gaze-based assistive systems due to their disabilities and their need of emotion recognition systems, the performance of our emotion recognition system in terms of judging "negative" or "not negative" expression can provide the same benefit.

When the emotion recognition system is used as a communication tool between children with PIMD and others, the emotions must be recognized using the data acquired from sensors on site and in real time. Low physical burden sensors are used in the system and can be integrated into medical devices that children with PIMD use daily. We confirmed that the RF classifier for the emotion recognition has a short computation time that is sufficient for communicating with children in real time using a standard laptop computer. Therefore, the emotion recognition system is feasible as a communication tool for hardware and software.

Limitation and future works

Obtaining the true emotions of children with PIMD is extremely difficult. Therefore, the emotions are estimated by the estimators, who are likely to provide reliable emotions, and the system for outputting the estimated emotions from the inputs of physiological and motion signals is obtained through the AI learning process. In the future work, it will be possible to make the estimated emotion closer to the true emotion by increasing the number of estimators to integrate the emotion label, which will improve the system recognition rate. A correlation hint between the physiological and motion signals and the emotion of children with PIMD may be found if the number of participants is increased, and the system is modified.

Four major issues must be addressed in the future. The first one is the improvement of the system recognition rate by using other classifiers, such as artificial neural networks, considering real time processing and the required amount of data. The second issue is the analysis of data collected on different days and the identification of differences in the physiological characteristics based on that day. The third one is the determination of the reason for the system’s ability to recognize emotion and the validation of this reason. The fourth and last issue is the usage of automatic image processing to obtain the eye gaze and tongue motion instead of manual image processing.

Conclusion

In this study, we created a concept based on AI for the emotion recognition systems for children with PIMD by using physiological and motion signals, developed and tested an emotion recognition system based on the proposed concept using the RF classifier that took as inputs the RRI, eye gaze, and other data acquired using low physical burden sensors, and proposed the validated concept. The "negative" and "not negative" recognition rate of the developed system (i.e., 70.4% ± 6.1%) is higher than that of the unfamiliar person (i.e., 48.5% ± 5.0%). The result suggests that the proposed concept for the emotion recognition systems may be useful and valid for communicating with children with PIMD.

Disclosure Statement

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Table 1. List of the acquired physiological and motion signals.

Mean of RRI	S.D. of RRI	Maximum of RRI
Minimum of RRI	Skew of RRI	Kurtosis of RRI
Median of RRI	LF	HF
LF/HF	a of RRI = $at + b$	b of RRI = $at + b$
R^2 of RRI = $at + b$	Eye gaze	Tongue motion
Deep breath	iEMG (right leg)	iEMG (right arm)

Table 2. Emotion recognition rate of "negative" and "not negative" [%].

	1	2	3	4	Mean ± S.D.
Proposed system	61.6	68.1	75.7	76.4	*70.4 ± 6.1
Unfamiliar person	56.8	45.9	43.5	47.6	48.5 ± 5.0

*$p < 0.05$

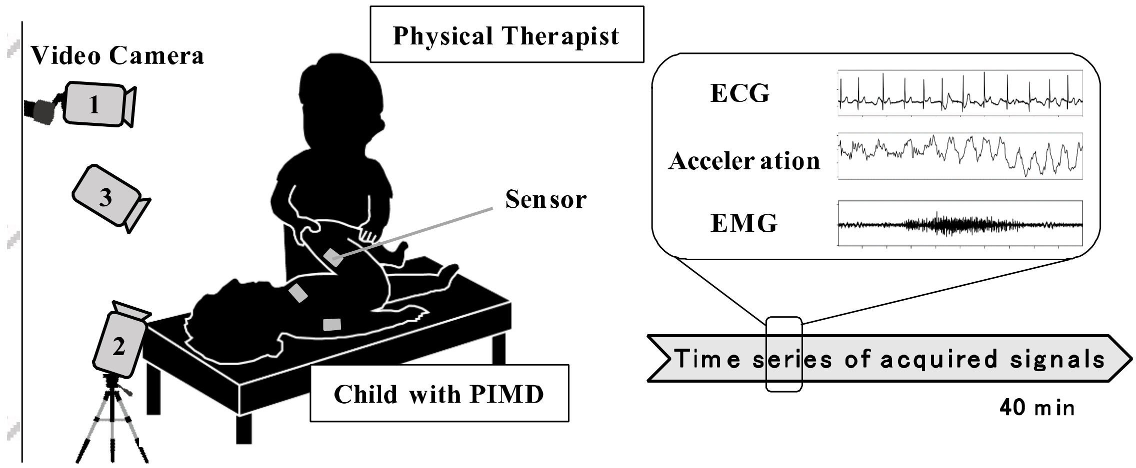

Figure 1. Overview of the experiment.

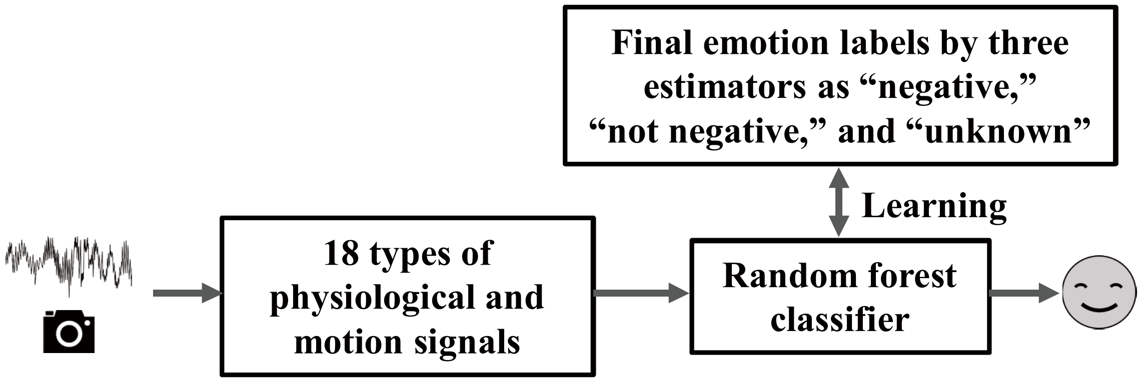

Figure 2. Overview of the developed emotion recognition system.

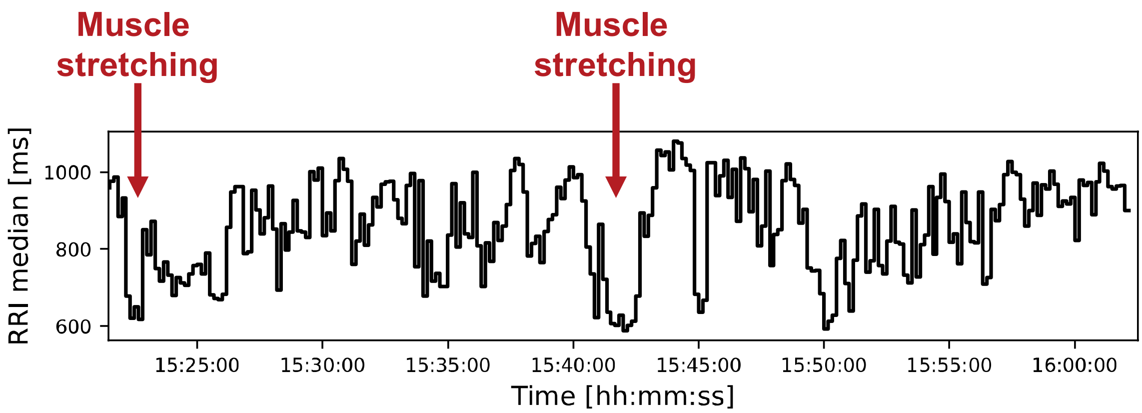

Figure 3. Time series of the median of RRI.

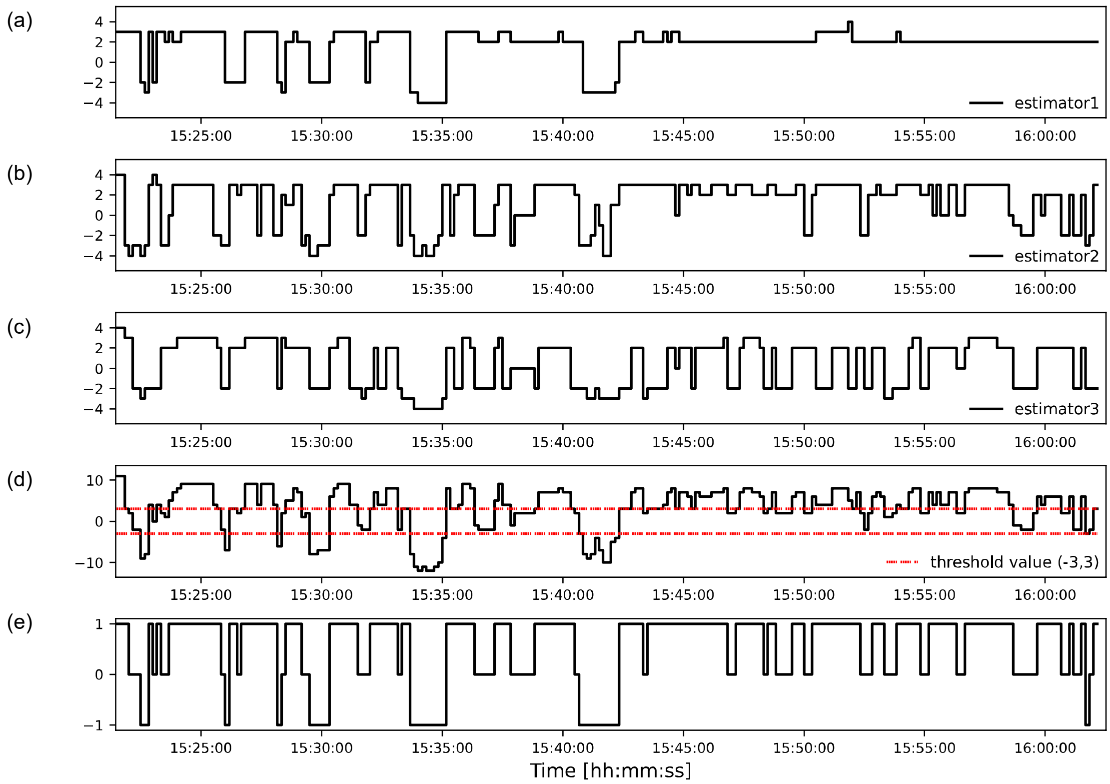

Figure 4. Time series of emotion label values by estimators. (a–c) The emotion label value with confidence estimated by each estimator. (d) The summed emotion label value of three estimators. (e) The final emotion label value.

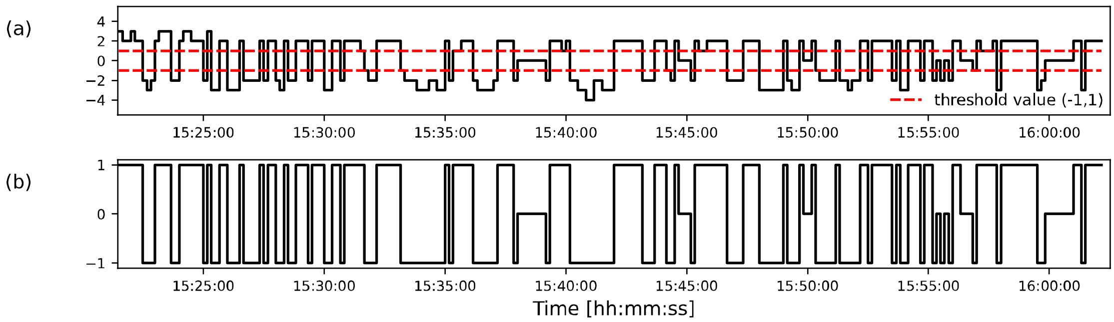

Figure 5. Time series of emotion label values by an unfamiliar person. (a) The emotion label value with confidence is estimated by an unfamiliar person. (b) The final emotion label value.