Evaluation of Distraction Effect of Music Stimuli During Cycling Exercise With Low Intensity in Terms of Multiple Time Scale

Caijilahu Bao∗, Zhiqiang Ma, Member, IEEE, Zhuoyi Wu, Wenjun Gao, Gwanggil Jeon∗∗, Senior Member, IEEE, and Tohru Kiryu, Life Member, IEEE

Abstract—There is a lack of research on the distraction effects of music stimuli with the multiple time scales of biological functions. It should be preferable to propose an effective strategy for evaluating the time-varying behavior (TVB) of psychological responses to music during exercise on autonomic nervous activity (ANA). From the RR interval time series of electrocardiograms recorded during cycling with low intensity, we estimated ANA-related indices: time- and frequency-domain indices estimated from the fluctuations of the RR interval. Then, we searched the temporal distribution of the stimulus-response module (SRM) that appeared in the TVB. The inspection of distraction effects was done for properly selected ANA. Then, related indices and the ratings of perceived exertion for evaluating appropriate participants are based on both the impression of favorability to music and the SRM occurrences. The results inferred that the multiple time scales strategy could be of help to assess the suitable approach to identify the distraction effects of music stimuli.

Index Terms—Distraction effect, multiple time scale, music stimuli, perceived exertion, physical effort.

I. INTRODUCTION

AN EFFECT of listening music on different psychological functions has been discussed in terms of relaxation and refreshment in stressful situations [1]–[5]. These findings support that listening to music could change the focus of attention but could not change the physiological fatigue level [6].

Manuscript received 30 April 2021; revised 27 December 2021 and 22 February 2022; accepted 6 March 2022. Date of publication 9 March 2022; date of current version 11 September 2023. This work was supported in part by the Scientific Research Project of Inner Mongolia University of Technology under Grant ZZ202119, and in part by the National Natural Science Foundation of China through Exploratory Research under Grant 61762070 and Grant 61862048. (Corresponding author: Caijilahu Bao.)

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of Niigata University. Caijilahu Bao, Zhiqiang Ma, Zhuoyi Wu, and Wenjun Gao are with the Department of College of Data Science and Application, Inner Mongolia University of Technology, Hohhot 010080, China (e-mail: bao-caijilahu@163.com).

Gwanggil Jeon is with the Department of Embedded Systems Engineering, Incheon National University, Incheon 22012, South Korea (e-mail: gjeon@inu.ac.kr).

Tohru Kiryu is with the Department of Graduate School of Science and Technology, Niigata University, Niigata 950-2181, Japan (e-mail: kiryu@eng.niigata-u.ac.jp).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TCDS.2022.3157915.

Digital Object Identifier 10.1109/TCDS.2022.3157915

Regarding the relationship between cycling exercise and simultaneous fatigue responses, Hayano et al. [7] reported that autonomic nervous activity (ANA) regulates physical activity levels based on cardiorespiratory interaction during cycling. Kiryu et al. [8] studied the overall behavior of the heart rate (HR) during cycling and rest periods in relation to the cardiorespiratory cycle, the muscle contractions, and the ratings of perceived exertion (RPE) under different workload intensities. On the basis of the current interpretation of the modulating effects, music is perceived as a diversion from unpleasant proprioceptive sensations that arise from physical effort. Moreover, Jones et al. [9] reported that attentional manipulations can exert a salient influence on effect and enjoyment even at intensities slightly above the ventilatory threshold but theories suggest that external stimuli (e.g., auditory and visual) may be rendered ineffective in modulating attention when exercise intensity is high. However, the different distractive effects reported in the above studies have made their interpretation uncertain. The disparities between these studies could be due to many factors, among which are the heterogeneity of study populations, interventions, outcome measures, etc. Moreover, there is a lack of research on the distractive effects of music with multiple time scales that should be applied to identify the most effective strategy for assessing them mainly via ANA.

Accordingly, we will adopt time-varying behavior (TVB) of ANA-related indices and multivariate analysis investigating the physiological and psychological responses to music stimuli during cycling. Our purpose is to conduct a feasibility study on a multiple time scales strategy that could clarify the distractive effects by determining suitable relationships among participants and physiological and psychological assessments.

II. METHODS

A. Participants

Fifteen healthy males (23.1 ± 2.6 years old) provided written informed consent to their participation in all procedures associated with the study. They reported that they had not received formal musical education and had not played any musical instrument within the last five years. In addition, they also reported that they did not like to do any physical activity on a normal day. They indicated to what extent they usually listen to music during walking or driving. The experimental
procedure and tasks were explained; details regarding the aims of the study or the variables of interest were omitted. Prior to the experiments, the ethical approval was granted by the ethics committee at Niigata University.

B. Experimental Procedure

By placing the surface electrode (Bs-150, Nihon Kohden Inc.) on the chest (V6), we recorded electrocardiogram (ECG) signals at a sampling frequency of 1000 Hz (Myomonitor IV, Delsys Inc.) for a cycling (60 rpm) trial with a bicycle ergometer (STB-1400, Combi Inc.). The workload was constant low-intensity cycling exercise (50 W) [10]. The music stimulus was jazz\(^1\) with a 135-bpm tempo, played through earphones and adjusted to a comfortable level (70–85 dB).

The sequence (Fig. 1) took a total of 22 min per trial: a participant performed a 5-min warm up of cycling without music stimuli and then took a 1-min rest to regulate HR; and five consecutive 3-min cycling tasks (T\# ) were then carried out while listening to music (T1–T5; total 15 min). The participants were given a questionnaire during each minute of the task, in which they were asked to rate their RPE. Finally, to evaluate the music impression, participants completed a 1-min simple questionnaire after the cycling exercise. We combined the five tasks into three overlapping phases (Fig. 1): 1) phase 1 (T1, T2, and T3); 2) phase 2 (T2, T3, and T4); and 3) phase 3 (T3, T4, and T5), shifting phases every 3 min.

C. Biosignal Processing

In the psychological questionnaire, the participants selected the appropriate RPE displayed in the panel on the handle every minute: Borg’s RPE (Fig. 2) ranging from 6 to 20 [11]. The music impression was defined on a scale ranging from 0 to 5 for 26 categories [12], [13]; and the total score ranged between 0 and 130.

For biosignal processing in the TVB of the psychological responses, we used a resampling (4 Hz) algorithm with cubic spline interpolation to obtain a uniformly sampled R-R interval (RRI) time series. For the fluctuation of RRI, i.e., HR variability (HRV), as the time-domain index, we estimated the total RRI, the mean RRI, the standard deviation of the RRI (SDNN), the root mean square of successive RRI differences (RMSSDs), and the SDNN/RMSSD ratio that would play a relative indicator of the sympathetic nervous activity [14], [15]. Estimating the frequency-domain indices, we used a continuous wavelet transform with a Gabor function controlling the time and frequency resolution. They were the low-frequency (LF) (0.04–0.15 Hz) and high-frequency (HF) (0.15–0.45 Hz) components as well as the LF/HF ratio, as the conventional indicators of ANA [16]. The ANA-related indices were then evaluated in the time and frequency domains every 10 s: the total number of samples was 90 for the five consecutive tasks. We introduced nonuniformly sampled TVB of ANA-related indices for a stimulus-response module (SRM) (Fig. 3) that could be composed of stimuli as a trigger point and the response as an accumulation section (AS) [17]. In the expected physiological meaning, the duration is short for stimuli, and longer for the response. When stimuli occur frequently within the duration of response, the responses are superimposed in time. This could be defined as an accumulation of physiological responses. Therefore, the occurrence of SRM indicates that physiological activities are sufficiently stimulated by external stimuli. The expected AS was surveyed based on the following SRM-related conditions: normalized LF component greater than 120% (LF120) and normalized HF component less than 80% (HF80) [17], [18]. The onset for AS (over a 2-s epoch) was estimated by tracing the TVB of the normalized LF component backward in time for locating the local minimum, as the time of the trigger point. Note that the indices were normalized by each mean for 3 min in the middle of the warm up. The measured data were analyzed using MATLAB R2014a (MathWorks Inc.) to estimate the physiological indices.

D. Statistical Analysis

The participants were divided into two groups based on the median of the total score (“favorite:” score ≥ median; “non-favorite:” score < median). Then, the differences between the two groups were evaluated by multiple regression analysis and factor analysis to evaluate the distraction effect of

\[^1\]Before the experiment, the participants were not informed of the stimulating music they listened to.
the stimulating music during exercise. The statistical analyses were performed using JMP 11 (SAS Institute Inc.).

In the multiple regression analysis, we used the ANA-related indices as explanatory variables to estimate the psychological index, RPE. Furthermore, to evaluate the distraction effect, we performed a correlation analysis to confirm the strong correlation between HR and RPE ($\gamma_{HR-RPE}$) [10]. In the factor analysis, the number of common factors on the physiological indices was determined as follows: factors whose eigenvalue was greater than 1.0 [19] were only retained for the variable loadings along with over 70% cumulative contribution ratios. A bivariate normal distribution was performed for each pair of factor score samples, and then a nonparametric density profile was observed performed for overlapping three phases in the two groups.

III. RESULTS

Based on the music impression score, the participants (15) were divided into favorite (8) and nonfavorite (7) groups by the median of music impression score, 82 (Fig. 4).

Furthermore, by observing the TVB of ANA-related indices, there were temporal distributions of 19 SRMs: 14 in favorites and 5 in nonfavorites. As a result, the number of occurrences in the favorite group was more than that in the nonfavorite one and the occurrences were more concentrated in phase 3 than in phases 1 or 2, that is, later in a trial (Fig. 5).

Fig. 6 depicts the TVBs of the measured RPE (mRPE) and the estimated RPE (eRPE) with the ANA-related indices employed in multiple regression equations. The mRPE showed it linearly increases until experimental segment T4 and tends to saturate at T5 in each group, and this trend was more explicit in eRPE. Moreover, the mRPEs in the nonfavorite group from T2 to T5 significantly (*$p < 0.05$, **$p < 0.01$) increased more than those in the favorite group (Fig. 7).

The correlation coefficient decreased from T1 to T3 and then increased from T3 to T4, after which the correlation coefficient becomes small or no correlation or inverse correlation at T5 (Table I). Moreover, except for the $\gamma_{HR-mRPE}$ on T3 and T4, the correlation coefficient of the favorite group was
TABLE II  
FACTOR STRUCTURE FOR ANA-RELATED INDICES AT THREE PHASES

| group     | phase # | factor # | eigenvalue | cumulative contribution ratio [%] |
|-----------|---------|----------|------------|-----------------------------------|
| favorite  | phase 1 | factor 1 | 5.23       | 0.65                              |
|           |         | factor 2 | 1.23       | 0.81                              |
|           | phase 2 | factor 1 | 3.47       | 0.43                              |
|           |         | factor 2 | 2.36       | 0.73                              |
|           | phase 3 | factor 1 | 3.04       | 0.38                              |
|           |         | factor 2 | 2.52       | 0.70                              |
| non-favorite | phase 1 | factor 1 | 5.38       | 0.67                              |
|           |         | factor 2 | 1.27       | 0.83                              |
|           | phase 2 | factor 1 | 4.30       | 0.54                              |
|           |         | factor 2 | 2.01       | 0.79                              |
|           | phase 3 | factor 1 | 4.30       | 0.54                              |
|           |         | factor 2 | 2.12       | 0.80                              |

Fig. 8. Nonparametric density contours for overlapping three phases in two groups: red line shows bivariate normal ellipse; the density range was determined to be 0.9.

smaller than that in the nonfavorite group on each task, and this phenomenon was more obvious on the γHR-eRPE.

In factor analysis, the two common factors, factors 1 and 2, were determined on the basis of the factor structure (Table II) and factor loading (Table III) of the ANA-related indices in the three phases.

In the favorite group, the time-domain indices, RRI, and HR, were active on factor 1, but not active on factor 2 during the three phases; SDNN and SDNN/RMSSD were active on factor 2 in phase 2, but not active during any of the other phases. The frequency-domain indices, LF and LF/HF, were active on factor 2 during phases 1 and 3; HF was active on factor 2 in phase 3. In the nonfavorite group, the time-domain indices, RRI, and HR, were active on factor 1 in phases 1 and 3. SDNN and SDNN/RMSSD were active on factor 1 in phase 2, while RMSSD was active on factor 2 in phase 1. The frequency-domain index, LF, was active on factor 2 in phase 3, while HF was active on factor 2 in phases 1 and 3. SDNN and SDNN/RMSSD were active on factor 1 in phase 2, while RMSSD was active on factor 2 in phase 1. The frequency-domain index, LF, was active on factor 2 in phase 3, while HF was active on factor 2 in phases 1 and 3. SDNN and SDNN/RMSSD were active on factor 1 in phase 2, while RMSSD was active on factor 2 in phase 1. The frequency-domain index, LF, was active on factor 2 in phase 3, while HF was active on factor 2 in phases 1 and 3. SDNN and SDNN/RMSSD were active on factor 1 in phase 2, while RMSSD was active on factor 2 in phase 1.

Fig. 8 shows the bivariate normal ellipse distribution of score samples for each pair of factors. In the favorite group, the scores are rather concentrated on the first factor in phase 3 and less on the second factor than that for other phases. In the nonfavorite group, from the nonparametric density, the scores were probably normally distributed on the first and second factors for the three phases.

IV. DISCUSSION

A. Evaluation of Distraction Effects With SRM in TVB of ANA-Related Indices

Time-domain measures were adopted to study sympathovagal balance during low-intensity cycling exercise [15]. They were particularly important in the context of HRV monitoring in real-time or ambulatory settings. Moreover, to characterize the autonomic response to musical stimuli, biosignal processing in time and frequency domains has been simultaneously provided [20].

Regarding the autonomic responses, spectral analysis appeared to demonstrate more sensitive and enlightening

TABLE III  
FACTOR LOADINGS FOR ANA-RELATED INDICES

| group      | phase # | phase 1 | phase 2 |
|------------|---------|---------|---------|
| indices    | factor 1 | factor 2 | factor 1 | factor 2 |
| RRI        | 0.93     | 0.28    |         |         |
| HR         | -0.94    | -0.24   |         |         |
| LF         | 0.50     | 0.78    |         |         |
| HF         | 0.50     | 0.60    |         |         |
| LF/HF      | 0.11     | 0.15    |         |         |
| SDNN       | 0.58     | 0.31    |         |         |
| RMSSD      | 0.69     | 0.29    |         |         |
| SDNN/RMSSD | 0.01     | 0.10    |         |         |

| non-favorite | phase 1 | phase 2 | phase 3 |
|--------------|---------|---------|---------|
| indices      | factor 1 | factor 2 | factor 1 | factor 2 |
| RRI          | 0.88     | 0.43    |         |         |
| HR           | -0.88    | -0.43   |         |         |
| LF           | 0.58     | 0.62    |         |         |
| HF           | 0.44     | 0.74    |         |         |
| LF/HF        | 0.11     | 0.15    |         |         |
| SDNN         | 0.39     | 0.62    |         |         |
| RMSSD        | 0.52     | 0.84    |         |         |
| SDNN/RMSSD   | 0.06     | 0.00    |         |         |

| group      | phase # | phase 3 |
|------------|---------|---------|
| indices    | factor 1 | factor 2 |
| RRI        | 0.97     | 0.03    |         |
| HR         | -0.98    | 0.03    |         |
| LF         | -0.02    | 0.85    |         |
| HF         | 0.18     | 0.85    |         |
| LF/HF      | -0.29    | 0.75    |         |
| SDNN       | 0.22     | 0.20    |         |
| RMSSD      | 0.41     | 0.21    |         |
| SDNN/RMSSD | -0.15    | 0.09    |         |

| non-favorite | phase 1 | phase 2 | phase 3 |
|--------------|---------|---------|---------|
| indices      | factor 1 | factor 2 | factor 1 | factor 2 |
| RRI          | 0.98     | -0.10   |         |         |
| HR           | -0.97    | 0.11    |         |         |
| LF           | -0.12    | 0.83    |         |         |
| HF           | -0.16    | 0.34    |         |         |
| LF/HF        | -0.01    | 0.34    |         |         |
| SDNN         | -0.10    | 0.51    |         |         |
| RMSSD        | 0.21     | 0.35    |         |         |
| SDNN/RMSSD   | -0.22    | 0.29    |         |         |
HRV indices compared with time-domain analysis [21]. Thus, we surveyed the occurrences of SRM in the TVB of the frequency-domain indices to verify the time distribution of physical effort-related autonomic regulation (Fig. 5). Since the LF and HF components stem from Mayer waves in blood pressure and respiratory sinus arrhythmia in respiration [7], they are expected to decrease and increase in stressful situations [8]. Therefore, the fluctuation of these components is the physiological evidence of blood pressure and respiration exchange. Regarding the SRM-related condition, AS would be inferred as an accumulation of physiological responses, because the LF/HF ratio, a relative indicator of sympathetic nervous activity, steadily increases or shows a saturating trend during exercise [2], [22]. Therefore, the occurrence of SRM indicates would be the sign that the participant is more high favorably highly favorable to stimulating music.

This approach would be suitable for localizing the temporal distribution of the SRM at each section. However, we do not yet conclude what types of ANA-related conditions could provoke this response during exercise with music. Different types of ANA-related indices would help to confirm the trigger points of SRM. Furthermore, faster music provoked responses with greater physiological effort than those with slower music or without music [23]. Karageorghis et al.’s research also mentioned walked at 70% of maximum HR reserve (maxHR) on a treadmill under three experimental conditions (medium tempo, fast tempo, and mixed tempo) and a no-music control. It was concluded that a medium tempo music program was the most appropriate for an exercise intensity of 70% maxHR and that each of the music preference experimental conditions yielded higher scores than the no-music control [9], [24]. There are many experiments [9], [24], [25] that prove that the subjects slow tempo music was not preferred at any exercise intensity, whereas preference for fast tempo increased as exercise intensity increased, but this is also bound by a certain threshold. In addition, the effect of music on exercise performance has been studied from many perspectives, but the results have not been as clear as expected, probably due to a lack of appropriate controls. In this study, we strictly controlled the conditions and all subjects listened to the same music under the same conditions to conduct experiments and investigated the distracting effects of music on the subjects. Corona and Aragón-Vargas’s [26] used individually selected preferred music in a carefully controlled environment, participants improved their spontaneous cycling performance only when the music had a fast tempo of 140 bpm.

Therefore, according to the temporal distribution of SRMs (Fig. 5), we believe that the multiple time scales strategy could be suitable to evaluate and highlight the effect of distraction on physiological effort. Moreover, the LF/HF ratio in the favorite group significantly (**p < 0.01) decreased than that in the nonfavorite group at every task (Fig. 9); 54 samples per group, this result was similar to that in previous reports [2], [22], [27]. As a result, the expected relaxation effects in the favorite group were more than those in the nonfavorite group. This suggests that greater distraction effects were due to favored music [2], [5], [6], [17], [22].

**B. Evaluation of Distraction Effects With Multivariate Analysis**

Borg’s RPE provides a useful way to reflect how hard a cycling task feels [11]. In fact, the increase in RPE was reported to be related to both the cardiovascular status monitored by HR and local muscle fatigue during stepping exercise [8], [28], [29]. Thus, we discuss the differences of RPE between two groups in terms of biosignal interpretation with multiple regression analysis. Referring to conventional procedures, participants became physically efforted as the cycling trial progressed, although they had different responses with multiple time scales to the stimulus music in terms of favorability. On the favorite group, the TVB of eRPE showed a saturating trend (Fig. 6) for the last tasks. It seemed to have a greater beneficial effect in relation to the distraction effect during the cycling exercise. Moreover, the γHR-eRPE in the favorite group was smaller than that in the nonfavorite group and appeared an inverse correlation or no correlation phenomenon. It suggested that RPE did not increase with favorite music even though physical effort would be induced.

To explain this evidence, we further performed a factor analysis of the ANA-related indices in three phases. From the results (Tables II and III), we speculated that the factor 1 was dominant in both RRI and HR, and the factor 2 was dominant among spectrum indices. The simple interpretation of these factors might be concluded that the factor 1 represented the mean of HR levels and factor 2 represented the variability of HR. However, from the strong correlation between RPE and HR, factor 1 was presumed to be awareness [1], [11], [21], [30]. Recently, Schmitt et al. accurately showed how individual patterns of spectral analysis of HRV changed, diverting fatigue states without fatigue conditions. They reported that the data analysis described the clustering of different types of effort levels through mathematical proximity of HR and the dominant variables of spectral analysis [21]. Consequently, we concluded that the second factor would infer physical effort. From this speculation, the scores were rather concentrated on the awareness factor at phase 3 and less on the physical effort factor than that for other phases in the favorite group. In the nonfavorite group, from the nonparametric density, the scores were probably normally distributed on the awareness and physical effort factors for the three phases (Fig. 8). These common factors have the potential to infer the relationships between
variables with a more efficient way to evaluate the distraction effects.

These results suggested that the music stimulus on the distraction effects appeared at two significant latent components that could be more directly assessed by a combination of self-reports and physiological effort-related measures and favorability factors. Therefore, nonuniformly modeling TVB of ANA-related indices is effective for evaluating the distraction effects without taking any unnecessary evaluation time.

In addition to the above discussion, to verify the relationship between real physical data and psychological data, we investigated TVB of measured RRI and HR in each group during 15 min cycling (Fig. 10). It is not difficult to find some doubts from the logic of Borg’s RPE. For example, in the comparison of Figs. 6 and 10, participants reported slightly higher RPE intensity at very low mean HRs.

We believe that this phenomenon is related to the living habits of the participants and their proficiency in the experiment (familiarity with music, etc.). Because the participants we selected were very young but found from the survey report that they had little interest in physical activity they often did research in the laboratory and do not like exercise and usually used public transportation or drove themselves to commute. In addition, we did not inform the experimental participants in advance about the stimulating music.2 There were also participants who did not have sufficient knowledge of the perceived effort value. From the above situation, we believe that the cardiorespiratory fitness index of the experimental participants is not very high and they may be unfamiliar with the stimulating music in this experiment. These objective and subjective factors will inevitably affect some of the doubts mentioned above. In order to avoid the occurrence of similar problems, in the future, we will find people with different physical conditions to adjust the exercise load (refer to the method of [31] and [32]) and the types of stimulating music to repeat this type of experiments to improve the practical value and scope of this research.

V. Conclusion

The expected distraction effects of music stimuli were assessed during low-intensity cycling exercise, evaluating the TVB of ANA-related indices in the time and frequency domains with multiple time scales. We tried to apply nonuniformly sampling to the TVB, defining an SRM observed in the time series of physiological events. Moreover, factor analysis and multiple regression analysis were used to reasonably select ANA-related indicators to infer the RPE of psychological events.

The present results showed that the multiple time scales strategy in revealing the progress of physical and mental effort could be of help to study the suitable approach, although further validation is required. Because the human body is not like a machine, his response ability will not be synchronized with time, and the response time is often slightly later than the time of being stimulated. Therefore, when investigating the human body stimulus-response study, it is necessary to analyze it on multiple time scales in order to obtain better and more accurate research results.

In the near future, this study combines robotics, artificial intelligence, biomedical engineering, and other fields to adjust the human body’s physiological and psychological balance to achieve the highest, best, and most efficient state. For example, during exercise, you do not need to choose the music (or video) rhythm, tempo, and exercise load by yourself. Instead, the machine analyzes your physical and psychological data and automatically recommends the best exercise mode for you.

These findings might lead to propose a better understanding of biological function with the multiple time scales. Then, other biosignals, such as muscle and brain activities should be investigated more, because the physiological indices are still not enough to explain the observed distraction effects as psychological responses.

ACKNOWLEDGMENT

The authors would like to thank all participants for participating in this experiment.

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Wenjun Gao received the B.E. degree in computer application technology from Hohai University, Nanjing, China, in 1995, and the M.E. degree in computer science and technology from Beijing Information Science and Technology University, Beijing, China, in 2007.

He joined the Inner Mongolia University of Technology, Hohhot, China, in 1995, where he is currently a Professor with the College of Data Science and Application. His research interests include speech recognition and natural language processing, with a special focus on emotional text generation.

Zhiqiang Ma (Member, IEEE) received the B.E. degree in computer application technology from Hohai University, Nanjing, China, in 1995, and the M.E. degree in computer science and technology from Beijing Information Science and Technology University, Beijing, China, in 2007.

He joined the Inner Mongolia University of Technology, Hohhot, China, in 1995, where he is currently a Professor with the College of Data Science and Application. His research interests include speech recognition and natural language processing, with a special focus on emotional text generation.

Prof. Ma is also a Reviewer of the Journal of Chinese Information Processing, IEEE ACCESS, and the International Computer Frontier Conference.
Gwanggil Jeon (Senior Member, IEEE) received the B.S., M.S., and Ph.D. (summa cum laude) degrees from the Department of Electronics and Computer Engineering, Hanyang University, Seoul, South Korea, in 2003, 2005, and 2008, respectively. From September 2009 to August 2011, he was with the School of Information Technology and Engineering, University of Ottawa, Ottawa, ON, Canada, as a Postdoctoral Fellow. From September 2011 to February 2012, he was with the Graduate School of Science and Technology, Niigata University, Niigata, Japan, as an Assistant Professor. From December 2014 to February 2015 and June 2015 to July 2015, he was a Visiting Scholar with the Centre de Mathématiques et Leurs Applications, École Normale Supérieure Paris-Saclay (ENS-Cachan), Cachan, France. From 2019 to 2020, he was a Prestigious Visiting Professor with the Centre de Mathématiques et Leurs Applications, École Normale Supérieure Paris-Saclay (ENS-Cachan), Cachan, France. From 2019 to 2020, he was a Visiting Scholar with the Dipartimento di Informatica, Università degli Studi di Milano Statale, Milan, Italy. He is currently a Full Professor with Incheon National University, Incheon, South Korea. He was a recipient of the IEEE Chester Sall Award in 2007, the ETRI Journal Paper Award in 2008, and the Industry-Academic Merit Award by Ministry of SMEs and Startups of Korea Minister in 2020. He is an Assistant Editor of Sustainable Cities and Society, IEEE ACCESS, Journal of Real-Time Image Processing, Journal of System Architecture, and Remote Sensing (MDPI).

Tohru Kiryu (Life Member, IEEE) received the B.E. and M.E. degrees in electronics engineering from Niigata University, Niigata, Japan, in 1975 and 1977, respectively, and the Dr.Eng. degree in computer science from Tokyo Institute of Technology, Tokyo, Japan, in 1985. From 1977 to 1978, he was an Assistant with the School of Dentistry, Niigata University, where he was with the Department of Information Engineering, from 1978 to 1995, and has been a Professor with the Graduate School of Science and Technology since 1995. From June 1990 to March 1991, he studied with the NeuroMuscular Research Center, Boston University, Boston, MA, USA, as a Visiting Scientist. He was working on biosignal processing, especially for understanding physical activity from myoelectric signals and heart rate variability during exercise and rest in field experiments. His current research interests include fatigue evaluation at a required time and place by a wearable measurement and Internet technology.

Dr. Kiryu is a member of the International Society of Electrophysiology and Kinesiology; the Institute of Electronics, Information, and Communication Engineers of Japan; the Japanese Society of Medical and Biological Engineering; and the Japan Society of Biomechanisms.