International Journal of Electrical and Electronic Engineering & Telecommunications Vol. 10, No. 4, July 2021

Measurement Method for Erector Spinae Muscle Activity during Patient Handling Using Inertial Sensor and Shoe-type Force Sensor

Kodai Kitagawa[1], Koji Matsumoto[1], Kensuke Iwanaga[1], Siti Anom Ahmad[2], Takayuki Nagasaki[3], Sota Nakano[4], Mitsumasa Hida[1,5], Shogo Okamatsu[1,6], and Chikamune Wada[1]
[1] Graduate School of Life Science and System Engineering, Kyushu Institute of Technology, Kitakyushu, Japan
[2] Malaysian Research Institute of Ageing (MyAgeing™), Universiti Putra Malaysia, Selangor, Malaysia
[3] Department of Rehabilitation, Tohoku Bunka Gakuen University, Sendai, Japan
[4] Department of Rehabilitation, Kyushu University of Nursing and Social Welfare, Tamana, Japan
[5] Department of Physical Therapy, Osaka Kawasaki Rehabilitation University, Kaizuka, Japan
[6] Department of Physical Therapy, Kitakyushu Rehabilitation College, Kanda, Japan
Email: {kitagawakitagawa156; ken.iwanaga.bat511; shogo.okamatsu182505}@gmail.com; matsumoto.koji593@mail.kyutech.jp; sanom@upm.edu.my; nagasaki@rehab.tbgu.ac.jp; nakano@kyushu-ns.ac.jp; hidam@kawasakigakuen.ac.jp; wada@brain.kyutech.ac.jp

Abstract—**Because caregivers often experience lower back pain caused by lumbar load from patient handling, monitoring this load can help prevent pain. Erector spinae muscle activity, which is measured and monitored as lumbar load, is commonly measured by electromyography (EMG). However, EMG's electrodes can cause skin irritation and be uncomfortable. Therefore, measuring muscle activity without electrodes is necessary. In this study, we propose a method for estimating erector spinae muscle activity using wearable sensors, specifically inertial and shoe-type force sensors. Inertial sensors measure acceleration and angular velocity of the trunk. Shoe-type force sensors measure vertical force of the feet. A regression model obtained from a machine learning algorithm can predict erector spinae muscle activity using inertial and force data. In our experiment, we evaluated the accuracy of our method by comparing sensor data with surface EMG data in patient handling. Results show that this method can measure erector spinae muscle activity with a small error (less than 5% maximal voluntary contractions) and a significantly high correlation with actual value (r = 0.891, p <0.05). In addition, a Bland-Altman plot showed no fixed and proportional errors. These findings indicate that our proposed method can accurately monitor the lumbar loads of caregivers.**

Index Terms—**Erector spinae muscle, inertial sensor, lumbar load, machine learning, muscle activity, shoe-type force sensor**

I. Introduction

Caregivers often experience lower back pain during patient handling because these motions require awkward postures, such as bending and twisting [1], [2]. Thus, continuous monitoring of lumbar loads is necessary to prevent lower back pain.

Erector spinae muscle activity, a lumbar load related to lower back pain [3], has been measured by electromyography (EMG) to help prevent this pain among caregivers [4]. However, EMG electrodes can cause skin irritation and are uncomfortable [5]. Therefore, EMG is considered unsuitable for the continuous monitoring of erector spinae muscle activity, and a measurement method without electrodes is required.

Previous studies have developed measurement methods for muscle activity without using electrodes [6]-[8]. Deffieux *et al*. developed an ultrafast imaging device for muscle contraction that could measure *in vivo* muscle contraction with high space and time resolution; however, this device is unwearable due to its large size [6]. Han *et al*. developed a muscle stiffness sensor using piezoelectric material and reported that a high correlation exists between the output of this sensor and surface EMG (sEMG); nevertheless, this sensor has variance issues caused by skin tissue thickness [7]. Jugade *et al*. developed PDMS−ZnO flexible piezoelectric composites to solve these problems; nonetheless, challenges remain, such as nonlinearities and hysteresis [8]. Therefore, it is necessary to develop a more accurate wearable method to measure elector spinae muscle activity during patient handling.

Machine learning techniques have been applied to accurate measurement using wearable sensors [9], [10]. For example, Zago *et al*. successfully estimated kinematic parameters, such as turn speed and mechanical work during running, by using a combination of inertial sensors and a machine learning-based regression model [9]. In addition, Matijevich *et al*. estimated tibial stress during running with a combination of inertial sensors, shoe-type force sensors, and machine learning techniques [10].

Manuscript received January 1, 2021; revised January 22, 2021; accepted February 5, 2021.

Corresponding author: Kodai Kitagawa (email: kitagawakitagawa156@gmail.com).

©2021 Int. J. Elec. & Elecn. Eng. & Telcomm.

doi: 10.18178/ijeetc.10.4.283-287

Learning from these studies, we considered that a combination of inertial sensors, force sensors, and machine learning techniques could realize accurate and wearable measurements for kinematic parameters. Therefore, we propose and evaluate a measurement method for erector spinae muscle activity using these sensors and techniques.

II. Proposed Method

Fig. 1 shows a block diagram of our method. This method calculates erector spinae muscle activity during the patient-handling motion by using a regression model obtained from wearable sensors and a machine learning algorithm. Components of this method are described below.

A. Wearable Sensors (Input)

We selected inertial and shoe-type force sensors for our proposed method because previous studies have succeeded in measuring kinematic parameters by these means [9], [10]. We measured wearable sensor data at a 1kHz sampling rate.

An inertial sensor (Logical Product Co., Japan) was attached to the trunk because trunk movements such as bending relate to lumbar load [11]. This inertial sensor measured three-axial acceleration and angular velocity of the trunk for features of the regression model.

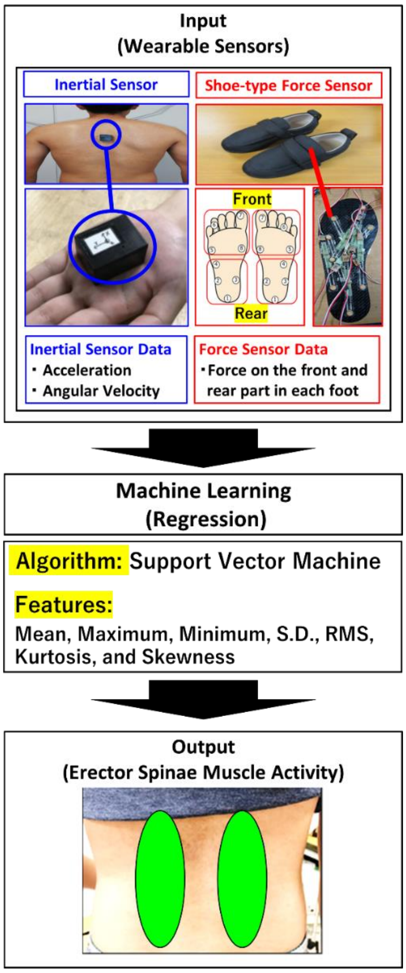

Fig. 1. Block diagram of the proposed method.

A shoe-type force sensor measured the ground reaction force that relates lumbar load during manual handling [12]. Insoles with 8 FlexiForce sensors (Tekscan, USA) were inserted into each shoe. We considered these suitable for measuring the force on the insole because the sensors are thin and flexible [13] and can be applied to real-time measurement because they have no linearity, non-repeatability, and hysteresis [14]. These FlexiForce sensors were calibrated dynamically by load cell and strain amplifier. We measured front and rear forces on each foot for the regression model. Both front and rear forces were calculated as average of forces at 4 FlexiForce sensors.

B. Machine Learing−Based Regression Model

The proposed method calculated erector muscle spinae activity by a machine learning-based regression model using features obtained from the wearable sensors. Support Vector Machine (SVM) was selected as the algorithm because SVM can provide high data performance in a small sample size [15]. Furthermore, SVM was used for previous study related to human movements and wearable sensors [9], [16].

We calculated the mean, maximum, minimum, standard deviation, root mean square, kurtosis, and skewness for each wearable sensor signal. These features were selected by our previous study that examined inertial and shoe-type force sensors [16]. The SVM and regression model were performed and validated by WEKA, which is a common data mining software [17]. Table I shows the SVM specifications and parameters used for our method.

C. Erector Spinae Muscle Activity (Output)

We measured actual values of erector spinae muscle activity using sEMG at the 1kHz sampling rate. We used these data to train and validate the machine learning algorithm.

We used Blue Sensor P (Ambu, Ballerup, Denmark) and EMG Logger LP-WS1402-W (Logical Product Inc., Fukuoka, Japan) to measure sEMG. Electrode locations for right and left erector spinae muscles were determined as per McGill [18]. We calculated integrated electromyographic (iEMG) values from the rectified signal of the sEMG and normalized these values temporally by dividing by the total time of each patient-handling motion and by using maximal voluntary contractions (MVC). Finally, we calculated mean values of right and left normalized iEMG as actual erector spinae muscle activity. This signal processing was performed using MATLAB R2020b (Mathworks Inc., Natick, MA, USA).

We used the normalized iEMG data for training and validation of the proposed method. If our method could accurately calculate muscle activity in validation, measurement of erector spinae muscle activity without sEMG would be realized.

TABLE I: SPECIFICATIONS AND PARAMETERS OF SVM

Specification/parameter	Status/value
Training	Sequential minimal optimization
Kernel	Polynomial kernel (order three)
c (weight for slack variable)	1.0

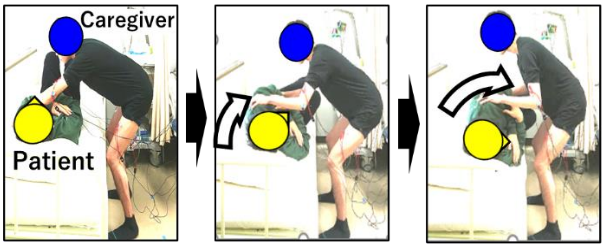

Fig. 2. Patient-handling motion in the experiment.

III. Experiment

In our experiment, we validated whether the proposed method could accurately measure erector spinae muscle activity during patient-handling motion.

A. Participants

The participants acting as caregivers were four young, healthy men (24.75 ± 0.83 years, 1.72 ± 0.05 m, 67.00 ± 10.79 kg). None had experiences as caregivers. One young, healthy man (25.00 years, 1.69 m, 70.00 kg) participated as a simulated patient. All participants provided their verbal informed consent to the experiment.

B. Procedure

Fig. 2 shows the patient-handling motion in this experiment. The participants provided postural changes of a patient on a bed. We selected this motion because it causes lower back pain in caregivers [19]. Each participant performed this motion for 10 trials. We measured the data from the wearable sensors and sEMG for actual erector spinae muscle activity during each motion.

C. Statistical Analysis

Our proposed method calculated erector spinae muscle activity by data obtained from 40 trials. We performed training and validation using 10-folds cross validation in WEKA [17]. We calculated the mean absolute error (MAE) of muscle activity between the proposed method and actual value, as well as Spearman's rank correlation coefficient, to evaluate accuracy.

Furthermore, we evaluated the fixed and proportional errors of our proposed method using a Bland−Altman plot. Using this plot, we calculated limits of agreement (LOA) to evaluate fixed errors. We used Spearman's rank correlation coefficient of this plot to evaluate proportional errors. We performed these statistical analyses using EZR [20], with $p<0.05$ considered as significant.

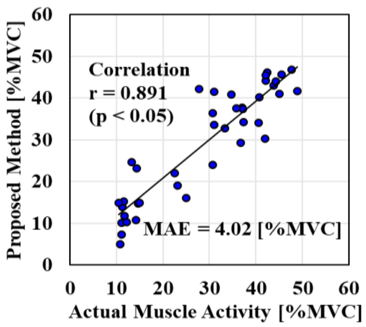

Fig. 3. Scatter plot of erector spinae muscle activity: where the solid line represents shoes regression line obtained from linear regression.

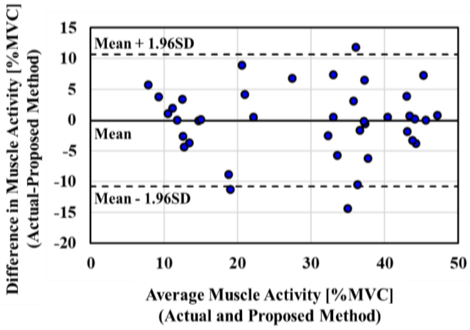

Fig. 4. Bland−Altman plot: Solid line shows mean of difference. Dashed lines show limits of agreement (LOA).

IV. Results

Fig. 3 shows the scatter plot of erector spinae muscle activity. The MAE of the proposed method was 4.02% MVC. A significantly high correlation exists between muscle activity calculated from the proposed method and actual value (r = 0.891, p<0.05). These results show that the proposed method could measure muscle activity close to actual value.

Fig. 4 shows the Bland−Altman plot. In the Bland-Altman plot, when LOA include zero, there is no fixed error. In addition, significant correlation between difference and average in the Bland-Altman plot indicates proportional error. This result shows there is no fixed error because LOA of this Bland-Altman plot includes zero. Furthermore, this result shows no proportional error because there is no significant correlation between difference and average of this Bland-Altman plot (r = 0.0675, p > 0.05).

V. Discussion

Results showed that our proposed method could predict erector spinae muscle activity with a small error (<5% MVC) and a significantly high correlation with the actual value (r = 0.891, p < 0.05). The variation of erector spinae muscle activity during patient-handling motion is larger than the error of our proposed method [21]. Furthermore, the results of the Bland−Altman plot showed no fixed or proportional errors. From these results, our proposed method can be applied to measure erector spinae muscle activity without electrodes. In addition, a combination of wearable sensors and machine learning techniques is effective for muscle activity measurement.

Our proposed method measured erector spinae muscle activity using only inertial and shoe-type force sensors. Our previous study proposed a posture recognition method for caregivers using these wearable sensors [16]. Therefore, a wearable prevention system for lower back pain based on biofeedback for lumbar loads and posture guidance can be realized using these methods.

One of the limitations of this study was that our proposed method was applied to only one patient-handling technique. This should be tested and generalized for several other patient-handling motions related to lower back pain [19], [22]. In addition, the participants were only young men without experience with caregiving activities. Previous studies have reported that patient handling techniques differ depending on experience and gender [23]-[25]. Thus, our method should also be tested with actual caregivers in the clinical field. Moreover, this study evaluated only SVM as the machine learning technique. Other techniques using wearable applications such as artificial neural network and reduced error pruning tree (REPTree) [26], [27] should be evaluated and compared for our method.

VI. Conclusion

In this study, we proposed and evaluated the measurement method for erector spinae muscle activity during patient-handling motion using inertial sensors, shoe-type force sensors, and a machine learning technique. Results showed that our proposed method can measure erector spinae muscle activity with great accuracy. In addition, we found no fixed or proportional errors.

In future work, we will modify our proposed method through experiments using other patient-handling motions. Furthermore, we will develop a wearable prevention system for lower back pain among caregivers.

Conflict of Interest

The authors declare no conflicts of interest associated with this paper.

Author Contributions

Conceptualization: Kodai Kitagawa (K.K.), Takayuki Nagasaki (T.N.), Sota Nakano (S.N.), and Chikamune Wada (C.W.): Methodology, K.K., Siti Anom Ahmad (S.A.A.), and C.W.; Software: K.K., Koji Matsumoto (K.M.) and Kensuke Iwanaga (K.I.); Validation: K.K., K.M., and K.I., Formal analysis: K.K. and Mitsumasa Hida (M.H.); Investigation: K.K., K.M., K.I., T.N., S.N., M.H., Shogo Okamatsu (S.O.), and C.W.; Resource: C.W.; Data curation: K.K. and K.M.; Writing--original draft preparation: K.K.; Writing--review and editing: K.K., S.A.A., T.N., S.N., M.H., S.O., and C.W.; and Supervision: C.W. All authors have read and agreed to the final version of the manuscript.

Acknowledgment

The first author is grateful for a scholarship from the Nakatani Foundation for Advancement of Measuring Technologies in Biomedical Engineering.

References

[1] A. Holtermann, T. Clausen, M. B. Jørgensen, A. Burdorf, and L. L. Andersen, "Patient handling and risk for developing persistent low-back pain among female healthcare workers," *Scand. J. Work Environ. Health*, vol. 39, no. 2, pp. 164–169, Mar. 2013.

[2] S. Kai, "Consideration of low back pain in health and welfare workers," *J. Phys. Ther. Sci.*, vol. 13, no. 2, pp. 149–152, Dec. 2001.

[3] J. P. Callaghan, J. L. Gunning, and S. M. McGill, "The relationship between lumbar spine load and muscle activity during extensor exercises," *Phys. Ther.*, vol. 78, no. 1, pp. 8–18, Jan. 1998.

[4] K. Itami, T. Yasuda, Y. Otsuki, M. Ishibashi, and T. Maesato, "Development of a checking system for body mechanics focusing on the angle of forward leaning during bedmaking," *Educ. Technol. Res.*, vol. 33, no. 1–2, pp. 63–71, Nov. 2010.

[5] Y. H. Chiou, J. J. Luh, S. C. Chen, J. S. Lai, and T. S. Kuo, "The comparison of electromyographic pattern classifications with active and passive electrodes," *Med. Eng. Phys.*, vol. 26, no. 7, pp. 605–610, Sep. 2004.

[6] T. Deffieux, J. L. Gennisson, M. Tanter, M. Fink, and A. Nordez, "Ultrafast imaging of in vivo muscle contraction using ultrasound," *App. Phys. Lett.*, vol. 89, no. 18, p. 184107, Oct. 2006.

[7] H. Han, H. Han, and J. Kim, "Development of real-time muscle stiffness sensor based on resonance frequency for physical Human Robot Interactions," in *Proc. Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society*, San Diego, 2012, pp. 2367–2370.

[8] S. S. Jugade and S. M. Kulkarni, "PDMS–ZnO flexible piezoelectric composites for measurement of muscle activity," *Bull. Mater. Sci.*, vol. 1, no. 43, pp. 1–6, Aug.2020.

[9] M. Zago, C. Sforza, C. Dolci, M. Tarabini, and M. Galli, "Use of machine learning and wearable sensors to predict energetics and kinematics of cutting maneuvers," *Sensors*, vol. 19, no. 14, p. 3094, Jan. 2019.

[10] E. S. Matijevich, L. R. Scott, P. Volgyesi, K. H. Derry, and K. E. Zelik, "Combining wearable sensor signals, machine learning and biomechanics to estimate tibial bone force and damage during running," *Hum. Mov. Sci.*, vol. 74, p. 102690, Dec. 2020.

[11] W. S. Marras, K. G. Davis, and K. P. Granata, "Trunk muscle activities during asymmetric twisting motions," *J. Electromyogr. Kinesiol*., vol. 8, no. 4, pp. 247–256, Aug. 1998.

[12] J. M. Maines and R. F. Reiser, "Ground reaction force bilateral asymmetries during submaximal sagittal plane lifting from the floor," *Int. J. Ind. Ergon*., vol. 36, no. 2, pp. 109–117, Feb. 2006.

[13] A. M. Almassri, W. Z. Wan Hasan, S. A. Ahmad, A. J. Ishak, A. M. Ghazali, D. N. Talib, and C. Wada, "Pressure sensor: state of the art, design, and application for robotic hand," *J. Sensors*, vol. 2015, p. 846487, Dec. 2015.

[14] A. M. Almassri, W. Z. W. Hasan, and C. Wada, "Evaluation of a commercial force sensor for real time applications," *ICIC-ELB*, vol. 11, no. 5, pp. 421–426, May 2020.

[15] Z. Zheng, Y. Zeng, S. Li, and W. Huang, "Mapping burn severity of forest fires in small sample size scenarios," *Forests*, vol. 2018, vol. 9, no. 10, p. 608, Oct. 2018.

[16] K. Kitagawa, K. Matsumoto, K. Iwanaga, S. A. Ahmad, T. Nagasaki, S. Nakano, M. Hida, S. Okamatsu, and C. Wada, "Posture recognition method for caregivers during postural change of a patient on a bed using wearable sensors," *Adv. Sci. Technol. Eng. Sys. J.*, vol. 5, no. 5, pp. 1093–1098, Oct. 2020.

[17] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: an update," *ACM SIGKDD Explorations Newsletter*, vol. 11, no. 1, pp. 10-18, Nov. 2009.

[18] S. M. McGill, "Electromyographic activity of the abdominal and low back musculature during the generation of isometric and dynamic axial trunk torque: Implications for lumbar mechanics," *J. Orthopaed. Res*., vol. 9, no. 1, pp. 91–103, Jan. 1991.

[19] H. Wardell, "Reduction of injuries associated with patient handling," *Aaohn J*., vol. 55, no. 10, pp. 407–412, Oct. 2007.

[20] Y. Kanda, "Investigation of the freely available easy-to-use software 'EZR' for medical statistics," *Bone Marrow Transplant*., vol. 48, no. 3, pp. 452–458, Mar. 2013.

[21] A. Belbeck, A. C. Cudlip, and C. R. Dickerson, "Assessing the interplay between the shoulders and low back during manual patient handling techniques in a nursing setting," *Int. J. Occup. Safe. Ergon*., vol. 20, no. 1, pp. 127–137, Jan. 2014.

[22] B. Schibye, A. F. Hansen, C. T. Hye-Knudsen, M. Essendrop, M. Böcher, and J. Skotte, "Biomechanical analysis of the effect of changing patient-handling technique," *App. Ergon.*, vol. 34, no. 2, pp. 115-123, Mar. 2003.

[23] K. Kjellberg, M. Lagerström, and M. Hagberg, "Work technique of nurses in patient transfer tasks and associations with personal factors," *Scand. J. Work. Env. Hea.*, vol. 29, No. 6, pp. 468–77, Dec. 2003.

[24] S. E. Samaei, M. Mostafaee, H. Jafarpoor, and M. B. Hosseinabadi, "Effects of patient-handling and individual factors on the prevalence of low back pain among nursing personnel," *Work*, vol. 56, no. 4, pp. 551-561, April 2017.

[25] A. C. E. Johnsson, A. Kjellberg, and M. I. Lagerström, "Evaluation of nursing students' work technique after proficiency training in patient transfer methods during undergraduate education," *Nurse Educ. Today*, vol. 26, no. 4, pp. 322-331, May 2006.

[26] S. Sivakumar, A. A. Gopalai, K. H. Lim, and D. Gouwanda, "Artificial neural network based ankle joint angle estimation using instrumented foot insoles," *Biomed. Signal Process. Control*, vol. 54, p. 101614, Sep. 2019.

[27] B. Cvetkovi, R. Milić, and M. Luštrek, "Estimating energy expenditure with multiple models using different wearable sensors," *IEEE J. Biomed. Health. Inform*, vol. 20, no. 4, pp. 1081-1087, May 2015.

Copyright © 2021 by the authors. This is an open access article distributed under the Creative Commons Attribution License (CC BY-NC-ND 4.0), which permits use, distribution, and reproduction in any medium, provided that the article is properly cited, the use is non-commercial, and no modifications or adaptations are made.

Kodai Kitagawa received his M.Eng. degree from the Kyushu Institute of Technology, Japan, in 2019. He is currently a Ph.D. student at the Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Japan. His current research interests include biomedical engineering, physical therapy, wearable sensing, and occupational health. He is a member of the Engineering in Medicine and Biology Society of the Institute of Electrical and Electronics Engineers (IEEE EMBS), the Society of Physical Therapy Science (SPTS), and the Rehabilitation Engineering Society of Japan (RESJA).

Koji Matsumoto received his M.Eng. degree from the Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Japan, in 2020. His current research interests include biomedical engineering, rehabilitation, and wearable sensing.

Kensuke Iwanaga received his B.Eng. degree from the Kyushu Institute of Technology in 2020. He is currently a master student at the Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Japan. His current research interests include biomedical engineering, control, and robotics.

Siti Anom Ahmad is an associate professor at the Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia. She received her B.Eng. degree in electronic/computer from Universiti Putra Malaysia in 1999. And then she received her Ph.D. degree in electronics in 2009 and M.Sc. degree in microelectronics system design in 2004 all from the University of Southampton, UK. Her research interests include biomedical engineering, signal processing and intelligent control system.

Takayuki Nagasaki received his Ph.D. degree in engineering from Kyushu Institute of Technology, Japan, in 2017. He is a professor of the Tohoku Bunka Gakuen University. His research interests include physical therapy, assistive technology, and rehabilitation engineering. He is a member of the Japanese Physical Therapy Association (JPTA), the Society of Physical Therapy Science (SPTS), and the Rehabilitation Engineering Society of Japan (RESJA).

Sota Nakano received his Ph.D. degree in engineering from Kyushu Institute of Technology, Japan, in 2017. He is an associate professor at the Kyushu University of Nursing and Social Welfare. His research interests include physical therapy, assistive technology, and rehabilitation engineering. He is a member of the Japanese Physical Therapy Association (JPTA), the Society of Physical Therapy Science (SPTS), and the Rehabilitation Engineering Society of Japan (RESJA).

Mitsumasa Hida received his M.S. degree from the Kio University, Japan, in 2010. He is currently a Ph.D. student at the Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Japan. He is also lecturer at the Osaka Kawasaki Rehabilitation University. His research interests include physical therapy, pain management, and rehabilitation engineering. He is a member of the Japanese Physical Therapy Association (JPTA), the Society of Physical Therapy Science (SPTS), the Japanese Society for the Study of Chronic Pain (JSSCP), the Japanese Society for Electrophysical Agents in Physical Therapy (JSEAPT).

Shogo Okamatsu received his M.Eng. degree from the Kyushu Institute of Technology, Japan, in 2020. He is currently a Ph.D. student at the Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Japan. He is also teacher at the Kitakyushu Rehabilitation College. His current research interests include physical therapy, adapted sports, and rehabilitation engineering. He is a member of the Japanese Physical Therapy Association (JPTA).

Chikamune Wada received the B.Eng. degree in mechanical engineering from the Osaka University, Japan, in 1990 and the Ph.D. degree in biomedical engineering from Hokkaido University, Japan, in 1996. From 1996 to 2001, he was an assistant professor of the Sensory Information Laboratory, Hokkaido University. In 2001, he became an associate professor of Human-function Substitution System Laboratory, Kyushu Institute of Technology. Since 2016, he has been a professor of Human-function Substitution System Laboratory. His research interests include assistive technology, especially measuring human motion and informing the disabled people of the necessary information to improve their QOLs. He is a senior member of the Institute of Electronics, Information and Communication Engineers (IEICE).