Calf Fatigue Recognition in Heel-lift Exercise Using Video Sequences of Body Sway

Takuya Kamitani*, Masaya Kojima* and Masashi Nishiyama*
* Graduate School of Engineering, Tottori University, Tottori, Japan, {takuya.kamitani,nishiyama}@tottori-u.ac.jp

***Abstract*—Previous analytical studies have investigated the relationship between calf fatigue and body sway measured using a force plate. However, they did not consider multiple levels of calf fatigue. Here, we propose a method for recognizing multiple levels of calf fatigue based on video sequences of body sway acquired using an overhead camera after the heel-lift exercise. For calf fatigue recognition, we extract a feature of body sway by generating a time-series signal of the head center position in the left-right and front-back directions based on medical knowledge. To evaluate the accuracy of our method, we created a dataset of 100 video sequences (20 participants $\times$ 5 calf-fatigue levels). The results show that our method can correctly recognize the calf-fatigue level with an accuracy of 40.0$\pm$1.8%. Furthermore, we demonstrated that for calf fatigue recognition, the accuracy of our method is superior to those of existing methods designed for human action recognition.**

I. Introduction

The calf, which plays a significant role in pumping blood to the heart [1], can sometimes cause poor blood circulation [2]. The heel-lift exercise can be performed to improve poor blood circulation in the calf. Here, we develop a method that gives feedback on the fatigue level of calf muscles after the heel-lift exercise based on video sequences acquired using an overhead camera, as shown in Fig. 1.

To realize such feedback, a method for accurately recognizing the calf-fatigue level after the heel-lift exercise is required. In this paper, body sway measured from video sequences is used for calf fatigue recognition. Previous analytical studies [3], [4] have investigated the relationship between calf fatigue and body sway measured using a force plate. They found that several factors of body sway show different traits depending on the presence or absence of calf fatigue. However, these studies did not consider multiple levels of calf fatigue on body sway.

In this paper, we propose a method for recognizing the calf-fatigue level based on body sway measured from video sequences acquired after the heel-lift exercise. Five levels of calf fatigue are quantitatively represented via linear approximation based on the maximum number of heel lifts that an individual can perform. We design a method that integrates medical knowledge [3], [4] to extract features from the video sequences of body sway. Specifically, we extract a feature of body sway for calf fatigue recognition by generating a time-series signal of the head center position in the left-right and front-back directions. To evaluate the proposed calf fatigue recognition method, we created a dataset of video sequences of body sway for various calf-fatigue levels for 20 participants (18 males and 2 females). This paper validated calf fatigue recognition based on video sequences of body sway acquired after the heel-lift exercise. The experimental results confirmed that our method improves the accuracy of calf fatigue recognition by integrating medical knowledge into feature extraction.

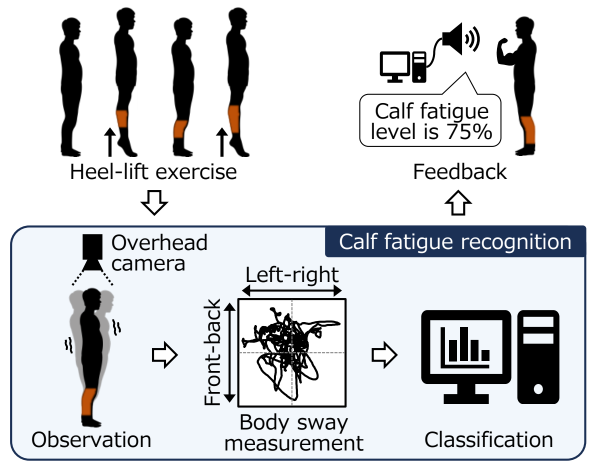

Fig. 1. Example of providing feedback on fatigue level of calf muscles using calf fatigue recognition.

II. Proposed Method

A. Calf-Fatigue Level Representation

For calf fatigue recognition, it is necessary to quantitatively represent the calf-fatigue level. Previous analytical studies [3], [4] represented calf fatigue in a binary manner, namely the presence or absence of calf fatigue. In this paper, we represent calf fatigue using multiple levels by assuming that the calf-fatigue level is directly proportional to the maximum number of heel lifts performed by an individual. The calf-fatigue level ranges from L_0 to L_{100}. A level of L_0 indicates that there is no fatigue in the calves (i.e., the person has refrained from vigorous exercise for a certain period). A level of L_{100} indicates that a person has just performed their maximum number of heel lifts. A level of L_{25} to L_{75} indicates that a person has just performed the heel-lift exercise up to 25% to 75% of their maximum number of heel lifts, respectively.

B. Validation Conditions of Heel-lift Exercise

We controlled the influence of the calf-fatigue level on body sway by setting the conditions of the heel-lift exercise as follows.

Initialization of calf fatigue level

The calves of the participant have no fatigue. A previous analytical study [5] reported that muscle loading causes muscle pain within 48 hours and that this muscle pain continues for 5 to 7 days. Here, we assume that muscle fatigue disappears when the associated muscle pain disappears. Thus, we set the rest period for the calves to ten days to allow as much muscle pain as possible to disappear.

Speed of heel lift

We set the heel lift speed to 100 beats per minute. We placed a device that emits a sound at a constant beat, similar to a metronome, near the participant. The participants were asked to raise and lower their heels in sync with this sound.

Height of heel lift

We set the heel lift height to 30% of each participant's foot length. We instructed the participants to follow the following three guidelines during the heel-lift exercise. (i) The head should touch a board placed at a height of the body height plus 30% of the foot length when the heels are lifted to prevent heel lift height variation. (ii) The eyes should be kept on the designated marker during the heel-lift exercise to prevent height variation due to changes in head orientation. (iii) Bending of the knees while lifting the heels should be avoided to prevent height variation.

Stop condition for heel-lift exercise

We set two stop conditions for the heel-lift exercise. The participants were asked to stop the heel-lift exercise when at least one of the conditions was met. The first condition was that the participant could not reach the head board with their head three consecutive times or that the participant voluntarily decided to stop the exercise. The second condition was that the participant performed a predetermined number of heel lifts (associated with L_{25}, L_{50}, or L_{75}).

Order for observing calf-fatigue levels

We determined the following order for observing calf-fatigue levels. First, we observed L_0. Then, we observed L_{100} and counted the maximum number of heel lifts required to reach this level. Then, we observed L_{25}, L_{50}, and L_{75}. To prevent the influence of previous calf-fatigue levels on the observation of the fatigue level of interest, we set the rest period between observations to 10 days.

C. *Procedure for Calf Fatigue Recognition*

There are no existing methods for calf fatigue recognition using video sequences of body sway (see Section I). A method [6] that uses video sequences of body sway to recognize the weight of baggage held by a person has been reported. However, we do not expect this method to have high accuracy in calf fatigue recognition because it was designed to distinguish baggage weight based on body sway (i.e., it lacks information on calf fatigue).

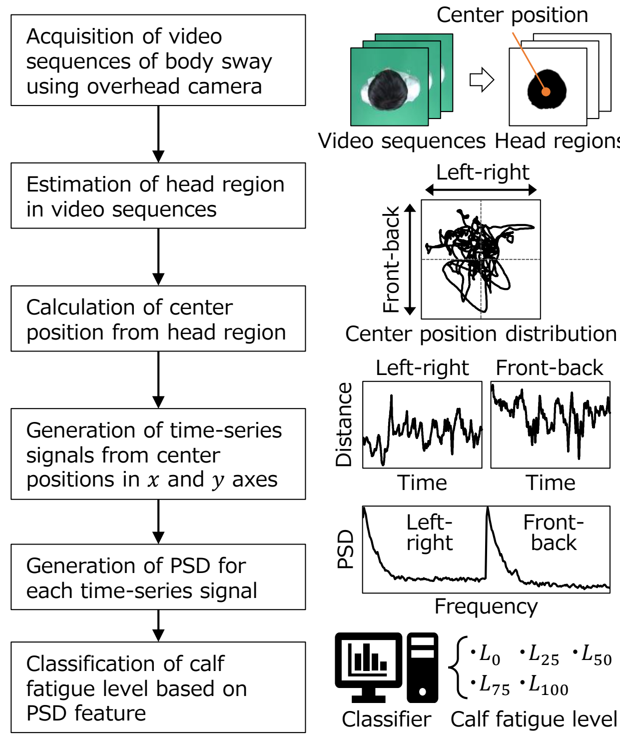

Fig. 2. Procedure of proposed method for calf fatigue recognition with medical knowledge integrated into feature extraction.

Here, we integrate medical knowledge on calf-fatigue levels reported in previous analytical studies [3], [4] into the feature extraction of an existing recognition method [6]. Previous analytical studies represented body sway as a time-series signal of the center of pressure (CoP) measured using a force plate. They reported that the left-right and front-back components of the CoP signals show different traits depending on the calf-fatigue level. In the proposed method, we use the center position of a participant's head region instead of the CoP. We hypothesize that the left-right and front-back components of the head center position also show different traits depending on the calf-fatigue level. We expect that extracting features from the left-right and front-back movements of the time-series signals of the head center position separately will improve the accuracy of calf fatigue recognition.

An overview of the proposed method for calf fatigue recognition is shown in Fig. 2. First, we estimate the participant's head region in each frame of the video sequence of body sway. Second, we compute the center position from the head region in each frame. Next, we separately generate time-series signals from the center position along the x and y axes of the image. The x and y axes represent body movement in the left-right and front-back directions, respectively. Note that the origin is set to the average point of the center position. Then, we obtain the power spectral density (PSD) of each time-series signal. Here, we apply a low-pass filter (from DC to 3 Hz) to each PSD to extract the principal frequency components of body sway, as done in previous analytical studies [7].

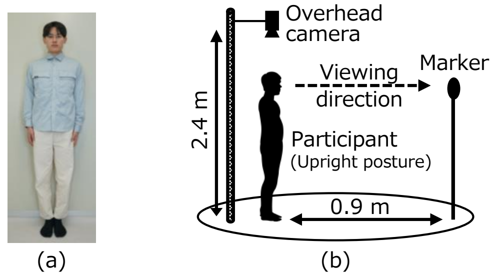

Fig. 3. (a) Photograph of participant and (b) observation settings used for obtaining dataset of video sequences of body sway for various calf-fatigue levels.

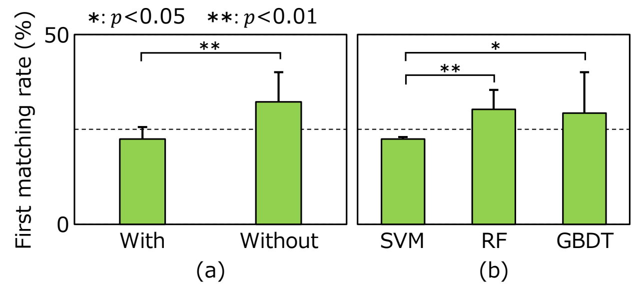

Fig. 4. Accuracy of calf fatigue recognition. (a) Results obtained with and without medical knowledge integration and (b) results obtained for various classifiers. $*$ denotes a significance level of 5% and $**$ denotes a significance level of 1%.

We extract a feature by concatenating the PSDs in the left-right and front-back directions. Finally, we perform the calf fatigue recognition by inputting the feature into a classifier to determine the calf-fatigue level (L_0 to L_{100}).

III. Experiments

A. Dataset

To evaluate the accuracy of the proposed calf fatigue recognition method, we created a dataset of the video sequences of body sway for various calf-fatigue levels. We recruited 20 participants (age: 22.4 ± 0.8 years, height: 167.4 ± 5.9 cm, weight: 60.7 ± 12.0 kg, ethnicity: Japanese) and instructed them to wear the designated light-blue shirt (see Fig. 3(a)). The experimental settings for observing participants are shown in Fig. 3(b). We instructed all participants to maintain an upright posture and focus on a marker placed in front of them while they were being observed. We set their standing position to be directly below an overhead camera.

We configured the overhead camera to record videos at a resolution of 1920×1080 pixels and 30 frames per second. To remove unnecessary background regions from the video sequences, we cropped all frames to 200×200 pixels. We observed each participant once per calf-fatigue level and set the observation time to 120 seconds. Finally, we acquired a dataset of 100 video sequences (20 participants $\times$ 5 calf-fatigue levels). Note that we observed the participants under the conditions described in Section II-B.

B. Evaluation of Calf Fatigue Recognition Method

We performed two sets of calf fatigue recognition experiments to evaluate the effectiveness of our method. In the first set, we compared the accuracy obtained with and without the integration of medical knowledge into the feature extraction. In the second set, we assessed the accuracy differences among several classifiers in recognizing calf-fatigue levels. For the first set of experiments, we set the conditions of the medical knowledge integration as follows.

- With medical knowledge integration: This is the proposed method. We used the feature described in Section II-C.
- Without medical knowledge integration: We utilized an existing feature [6] extracted from a time-series signal using frame differences to represent a participant's head movement for comparison. Even though this feature was designed to distinguish the weight of baggage held by a person, we directly applied it to recognize the calf-fatigue level without any modification.

For the second set of experiments, we set the conditions of the classifiers as follows.

- Support vector machine (SVM) [8]: We used a linear kernel and set the regularization value to 10.
- Random forest (RF) [9]: We set the number of decision trees to 300 and one of the feature selections to 30.
- Gradient boosting decision tree (GBDT) [10]: We set the number of weak classifiers to 300 and one of the feature selections to 30.

We split our dataset into testing and training sets using the leave-one-participant-out approach. Specifically, from the 20 participants, we assigned 1 participant to the testing set and the remaining 19 participants to the training set. We repeated this process 20 times (i.e., each participant was assigned to the testing set). We predicted the calf-fatigue level for each testing set and computed the first matching rate by aggregating all 20 predictions. Because of random sampling in RF and GBDT, we performed the prediction per participant by averaging 20 prediction trials.

We evaluated the accuracy of the calf fatigue recognition method using features with and without medical knowledge integration. We combined each feature with SVM, RF, and GBDT, respectively. Then, we calculated the average and standard deviation of the first matching rate from all combinations for each feature. Figure 4(a) shows the results of the calf fatigue recognition with and without medical knowledge integration. The average accuracy of the existing feature (without medical knowledge integration) was $22.5 \pm 3.1\%$ and that of our feature (with medical knowledge integration) was $32.3 \pm 7.8\%$. We examined whether there was a significant difference between these accuracies by applying the Wilcoxon signed-rank sum test. The test showed a significant difference in accuracy between the features with and without medical knowledge integration. These results show that integrating medical knowledge associated with calf fatigue into the feature extraction of body sway improves calf fatigue recognition.

Next, we evaluated the accuracy of calf fatigue recognition for each classifier. We combined SVM with the features with and without medical knowledge integration, respectively. Then, we calculated the average and standard deviation of the first matching rate for all combinations. For comparison, we also performed the same procedure for RF and GBDT. Figure 4(b) shows the results of calf fatigue recognition for each classifier. The average accuracy for SVM, RF, and GBDT was $22.5 \pm 0.5\%$, $30.3 \pm 5.2\%$, and $29.3 \pm 10.7\%$, respectively. We confirmed signification differences in the accuracy among these classifiers by applying the Wilcoxon signed-rank sum test and the Bonferroni correction for multiple comparisons. The tests showed significant differences in accuracy between SVM and RF and between SVM and GBDT. These results show that applying RF or GBDT as the classifier to combine with features extracted from body sway improves calf fatigue recognition compared with that obtained with SVM.

C. Comparison with Existing Methods Designed for Human Action Recognition

We attempted to recognize calf-fatigue levels from video sequences of body sway using existing methods [11]–[13] designed for human action recognition. Although these methods were not designed for calf fatigue recognition, we directly applied them for calf fatigue recognition since they were designed for recognizing class labels from video sequences. We expected these methods to have low accuracy in calf fatigue recognition. To confirm this, we evaluated the methods with the following settings.

- DI [11]: This dynamic image algorithm extracts a feature vector from a video sequence of body sway. A 40,000-dimensional weight feature vector was used to represent the temporal appearance changes using RankSVM. GBDT was used for classification.
- C3D [12]: This three-dimensional convolutional neural network extracts a feature map from a video sequence of body sway. A network structure with four 3D convolutional layers and four 3D pooling layers was used. Categorical cross entropy was used for classification.
- LSTM [13]: This long short-term memory network extracts a feature vector from a video sequence of body sway. A 128-dimensional feature vector calculated from the cell corresponding to the current time was used. Categorical cross entropy was used for classification.

For our method, the feature with medical knowledge integration and GBDT was used (see Section III-B). Note that the experimental conditions other than those given above were the same as those in Section III-B.

Table I shows the accuracy of the existing methods in calf fatigue recognition. The results confirm that our method achieved the highest accuracy. Therefore, our method extracts more informative features for calf fatigue recognition compared with those extracted by existing human action recognition methods. The results also confirm that integrating medical knowledge on calf fatigue into feature extraction improves the accuracy of calf fatigue recognition.

TABLE I
CALF FATIGUE RECOGNITION ACCURACY OF PROPOSED METHOD AND EXISTING HUMAN ACTION RECOGNITION METHODS.

Method	**Ours**	DI	C3D	LSTM
Accuracy(%)	$\mathbf{40.0 \pm 1.8}$	20.1 ± 2.1	16.8 ± 0.3	19.1 ± 2.3

IV. CONCLUSIONS

We validated calf fatigue recognition based on video sequences of body sway acquired after the heel-lift exercise. We extracted an informative feature for calf fatigue recognition by integrating medical knowledge, reported in previous analytical studies [3], [4], into the feature extraction of body sway. The experimental results show that our method can recognize five levels of calf fatigue with an accuracy of $40.0 \pm 1.8\%$. For calf fatigue recognition, the accuracy of our method is higher than those of existing methods [11]–[13] designed for human action recognition. Our method has potential applications in physical therapy, sports science, and personal fitness.

In future work, video sequences of participants of various ages will be collected. Furthermore, to expand the use case of our method, we plan to recognize calf-fatigue levels after exercises other than heel lifts. We appreciate Professor Yoshio Iwai for his valuable advice during this research.

REFERENCES

[1] D. E. Houghton, A. Ashrani, D. Liedl, R. A. Mehta, D. O. Hodge, T. Rooke, P. Wennberg, W. Wysokinski, and R. McBane, "Reduced calf muscle pump function is a risk factor for venous thromboembolism: a population-based cohort study," *Blood*, vol. 137, no. 23, pp. 3284–3290, 2021.

[2] M. H. Laughlin and B. Roseguini, "Mechanisms for exercise training-induced increases in skeletal muscle blood flow capacity : Differences with interval sprint training versus aerobic endurance training," *Journal of Physiology and Pharmacology*, vol. 59, no. 7, pp. 71–88, 2008.

[3] N. Vuillerme, N. Forestier, and V. Nougier, "Attentional demands and postural sway: the effect of the calf muscles fatigue," *Medicine and Science in Sports and Exercise*, vol. 34, no. 12, pp. 1907–1912, 2002.

[4] E. J. Bisson, D. McEwen, Y. Lajoie, and M. Bilodeau, "Effects of ankle and hip muscle fatigue on postural sway and attentional demands during unipedal stance," *Gait Posture*, vol. 34, no. 1, pp. 83–87, 2011.

[5] R. B. Armstrong, "Mechanisms of exercise-induced delayed onset muscular soreness a brief review," *Medicine and Science in Sports and Exercise*, vol. 16, no. 6, pp. 529–538, 1984.

[6] Y. Yamaguchi, T. Kamitani, M. Nishiyama, Y. Iwai, and D. Kushida, "Extracting features of body sway for baggage weight classification," *In Proceedings of IEEE 9th Global Conference on Consumer Electronics*, pp. 345–348, 2020.

[7] K. Taguchi, "Spectral analysis of body sway," *Journal for Oto-Rhino-Laryngology, Head and Neck Surgery*, vol. 39, no. 6, pp. 330–337, 1977.

[8] C. Cortes and V. Vapnik, "Support-vector networks," *Machine learning*, vol. 20, pp. 273–297, 1995.

[9] L. Breiman, "Random forests," *Machine learning*, vol. 45, pp. 5–32, 2001.

[10] J. H. Friedman, "Greedy function approximation: a gradient boosting machine," *Annals of statistics*, vol. 29, no. 5, pp. 1189–1232, 2001.

[11] H. Bilen, B. Fernando, E. Gavves, and A. Vedaldi, "Action recognition with dynamic image networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 40, no. 12, pp. 2799–2813, 2018.

[12] D. Tran, L. Bourdev, R. Fergus, L. Torresani, and M. Paluri, "Learning spatiotemporal features with 3d convolutional networks," *In Proceedings of the IEEE International Conference on Computer Vision*, pp. 4489–4497, 2015.

[13] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.