35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Feasibility Study on a Perceived Fatigue Prediction Dependent Power Control for an Electrically Assisted Bicycle*

T. Kiryu, *Member, IEEE*, and H. Minagawa

Abstract—**Several types of electric motor assists have been developed, as a result, it is important to control muscular fatigue on-site in terms of health promotion and motor rehabilitation. Predicting the perceived fatigue by several biosignal-related variables with the multiple regression model and polynomial approximation, we try to propose a self control design for the electrically assisted bicycle (EAB). We also determine the meaningful muscles during pedaling by muscle synergies in relation to the motion maturity. In field experiments, prediction of ongoing perceived physical fatigue could have the potential of suitable control of EAB.**

I. Introduction

Wearable and wireless measuring units and sensors [1, 2] as well as feedback systems [3] have been developed for the ubiquitous promotion of health and motor rehabilitation. However, these technologies are still limited in use because they are relatively expensive. This might be one of the reasons why subjectively presenting approaches instead of objectively measured data are used for recognizing the status of functional activities, instead of objectively measured data. The same thing has occurred in designing the power assistive systems. Several types of power assist systems have recently been proposed [4-6]. We have tried to develop a wearable unit for use as a biosignal-based control system, such as the cycle ergometer for the elderly [7] and electrically assisted bicycles (EAB) [8]. An assist system was created for the cycle ergometer that uses a fuzzy system that refers to the functional activities, such as the heart rate (HR) or rating of perceived exertion (RPE) to customize the workload pattern. On the other hand, the power assist design for the EAB has still not been created because it needs a control mechanism that can respond to both physical and topological variation changes. That is, where and when the power assist is required based on the functional activity needs to be considered in the design process. Thus, it needs on-site physical fatigue assessment. Guidelines for the speed, amount of power assist, and cadence are needed in the selection of an appropriate power assist mode (assist on/off, eco mode, and power assist mode) [9]. Thus, biosignals such as HR, VO_{2max}, and perceived exertion were used. A suitable type of power assist is expected when the muscle force for pedaling is insufficient, especially during uphill road climbing, where muscle fatigue causes a decrease in speed and cadence [10]. Using biosignals to estimate the amount of physical fatigue to control the amount and type of power assist has been proposed [6, 8, 9, 11]. We have tried to design a power assist system that is based on the physical fatigue estimated from the surface EMG (SEMG). There have been exoskeleton-type motion assist system [12] and ones for walking restoration [5, 13, 14]. Since enough power is obtained from these power assist systems, we now must focus on the design of the assist timing. Note that there are several types of delays between a motor command and the actual motion. However, suitable on-site muscle force and timing information for supporting degenerated muscle force for EABs is needed. There are gaps between the measurement and control due to several different biosignal time-scales. As a result, biosignal-based assist control delays should be considered [15]. Therefore, several ideas were suggested, such as adjusting the assist timing based on the crank angle and muscle activity [13], fuzzy control [4, 7], and feedback control by predicting VO_{2max} for controlling the cadence and power tracking control, to cope with this problem [16]. Prediction of the muscle activity is imperative for supporting muscle force when it is insufficient for a given motion before failure point is reached. There have been many studies for the estimation of muscle fatigue based on both the time and frequency domains. The key point is to design a measurement and control system that estimates and predicts the amount of fatigue based on the given biosignals, and then providing enough assistance in time.

The workload or assistance pattern for EABs is predetermined as a function of the biomechanical or physical parameters, such as the cadence or joint angles. Since individual differences in physical work capacity and the occurrence of muscle fatigue are not fully considered, there are occasions when the support for a needed assist and the assist timing is insufficient. This is the reason why we have tried to develop a biosignal-based power assist control system as a promising technology for providing the appropriate exercise levels for individuals in continuous exercise for the promotion of health and rehabilitation.

We tried to design a perceived physical fatigue dependent power control system for EABs in this study that is based on the feedback from the physical activities estimated from biosignals. First, we arranged for the ubiquitous measurement and evaluation of SEMG during dynamic exercise, by using the idea of muscle synergies. Second, we used biosignals to design a perceived physical fatigue-based workload control system.

II. Methodology

A. Biosignal Sensors Placement

The proper muscle activity during dynamic contractions will not be evaluated if the SEMG electrodes are placed in the wrong locations [7]. Thus, we started by measuring the bipolar SEMG signals from 15 channels array electrode during a squat exercise in which each electrode was placed 1

*Resrach supported by JSPS KAKENHI Grant Number 23650348.

Manuscript received April 2, 2013. T. Kiryu and H. Minagawa are with Graduate School of Science and Technology, Niigata University, Nishi-Ku, Niigata, 950-2181 Japan (e-mail: kiryu@eng.niigata-u.ac.jp).

978-1-4577-0216-7/13/$26.00 ©2013 IEEE

cm from the next (EMG-16, OT Bioeletronica). We placed a surface electrode on the skin that was separate from the active innervation zones after first detecting their locations. This approach was further confirmed by comparing three types of electrodes (two-bar, array, and matrix) during exercise in terms of the estimation of the conduction velocity of the motor unit action potential.

We recorded the ECG using a chest electrode V6 and the bipolar SEMGs from the lower limbs. The measurement system was composed of a 16 channels wireless unit (Myomonitor IV, Delsys) with the two-bar active electrodes (DE-2.1, Delsys) for the SEMG signals. Both the ECG and SEMG were sampled at 2000 Hz at a 16-bit resolution using the attachment software (EMGWorks 3.5, Delsys).

B. Evaluation of Muscle Activity during Exercise

We investigated the muscle activity in terms of a profile [18, 19] by sliding the motion dependent interval (e.g., 50 msec) every 10 msec for each pedal stroke. The profile was further normalized by using both the interval and the maximum amplitude in a trial after expressing the profile as a function of the knee joint angle or elapsed time for each stroke. Then the synchronously averaged percent profile for a segment consisted of several tens strokes in each phase. The parameters are the averaged rectified value (ARV), the root mean square (RMS), and the integrated EMG (*i*EMG). In addition, the mean power frequency (MPF) was estimated for each stroke. The muscle synergies are identified form synchronously averaged %RMS profiles in each phase. The torque, cadence, and speed were also estimated for each pedal stroke for evaluating the physical fatigue.

C. Muscle Synergies during Exercise

A similar motor control behavior by the agonist/antagonist muscle pairs is expected during the squat exercise. Target muscle identification was achieved by focusing on the muscle synergies, leading to the following process. We estimated the muscle synergies by looking at the non-negative matrix factorization in order to compare the behaviors of the agonist/antagonist muscle pairs. Assuming the %RMS profile $\boldsymbol{V}$ (i x j) from j muscles is modeled as

$$\boldsymbol{V} \approx \boldsymbol{W}\boldsymbol{H} \tag{1}$$

where $\boldsymbol{W}$ ($i \times r$) is muscle synergy profile, and $\boldsymbol{H}$ ($r \times j$) is the weight matrix. Then, setting the *k-th* vector of $\boldsymbol{H}$ as $\boldsymbol{h}_k$, the %RMS profile at the *k-th* muscle is obtained as follows:

$$\boldsymbol{v}_k \approx \boldsymbol{W}\boldsymbol{h}_k \tag{2}$$

We focused on the motion features of the knee joint during cycling by analyzing the *k-th* %RMS profile estimated from the *k-th* weight and synergy matrix. To identify the maturity and skill level, we used the correlation coefficients (CC) between the averaged %RMS of individual muscles and the muscle synergy profiles estimated from each group.

D. Subjective muscle fatigue Supported by Objectively Measured Data during Cycling

It should be noted that the measured data are affected by the location of the sensors [20]. Thus, information on the muscle activity is sometimes limited, although the measured biosignals are objective. Then, subjective data is important when it properly reflects the given situation of a vital function, such as physical fatigue. A multiple regression model is used to relate subjectively perceived fatigue with objectively measured data. The perceived physical fatigue for cycling could be modeled by referring to the incline of the slope geography [21]. The measured data would include HR and muscle activity variables. The multiple regression equation produces the time-series of the subjectively perceived fatigue. The perceived fatigue is assumed from the incline of the slope geography and modeled using the multiple regression equation using the HR, ARV, and MPF as follows:

$$\textit{Perceived fatigue} = a\mathrm{ARV} + b\mathrm{MPF} + c\mathrm{HR} + d \tag{3}$$

Further estimating the perceived physical fatigue as a function of time with a polynomial approximation produces the time-series from the previous several tens of cycling strokes. Then, it predicts the perceived physical fatigue every second by formularizing the time-series of the perceived fatigue by using the polynomials of the variables.

III. Results

The participants were informed of the risks involved in advance, and their ECG and muscle activity were monitored during the experiments. Each participant was further checked every ten strokes to determine whether or not the Borg's RPE [22] as a subjective index was over 20.

A. Muscle Synergies for determining Target Muscle

We used the muscle synergies from the muscle activities for eight agonist/antagonist lower limb muscles (vastus lateralis (VL), vastus medials (VM), biceps femoris (BF), semimembranosus (SEM), tibialis anterior (TA), gastrocnemius medials (GM), gastrocnemius laterials (GL), and soleus (SOL)) [23] to recognize the motion with the lower dimension. The subjects were asked to try to control the knee-joint extension and flexion every 4 s for up to 100 knee contractions during the squat exercise. Depending on the skill level, each subject showed a different habit to compensate for muscle fatigue. The habits include a multi-joint control for sustaining the given posture against the muscle fatigue. Five mature active rugby members and five immature university students were chosen in advance as the subjects for the estimation of the muscle synergies during the squat exercise.

The results showed that the third synergy showed a peak at the maximum knee flexion against the first synergy like that for a co-contraction during a full squat, which is different from those during a quarter squat and a parallel squat. The BF muscle showed an explicit significant difference in CC for the first and third synergies during a full squat. A peak appeared around the maximum knee extension and high factor loading occurred for the VL, VM, and TA muscles for the first synergy (#1). A peak appeared for the flection first and the extension last for the second synergy (#2). Using CC and the factor loadings, synergy #1 related to an agonist muscle contraction, whereas synergy #2 showed antagonist muscle contraction. For the matured subjects, the muscle activation pattern for BF approached that for a reciprocal contraction of VL [18, 23].

B. *Measurement of Biosignals during Cycling*

The employed EAB is designed to produce additional crank torque that is the same level as the rider-generated torque: (1:1) power assist. We used a 2100-m long circuit divided a 600-m uphill road into three phases (early, middle, and late phases including several tens (30-60) of consecutive contractions with different inclinations. Each trial was separated by 20-min rest intervals. Each participant was asked to keep the pedaling rate as close to 60 rpm as possible. We recorded the SEMG from the BF, VL, TA, and GM muscles during cycling.

Figure 1 shows the %RMS profiles for both daily exercise routine (ER) and non-ER subjects of VL and BF muscles, respectively. The cycling ER participant showed significant changes in muscle activity of VL. On the other hand, the non-cycling-ER participant showed changes in BF, which were similar to the results during squatting. We identified what muscle should be monitored using the estimated ARV and $\boldsymbol{h}_k$ during cycling outdoors (Figure 2). There was a significant decrease in the ARV and $\boldsymbol{h}_k$ of VL for each phase, but not for BF. On the other hand, the decrease in BF for each phase was significant for the non-ER subject, the decrease for BF in each phase was significant. As a result, EAB effect on the muscles was high for the VL and BF for the ER subject and the non-ER subject, respectively.

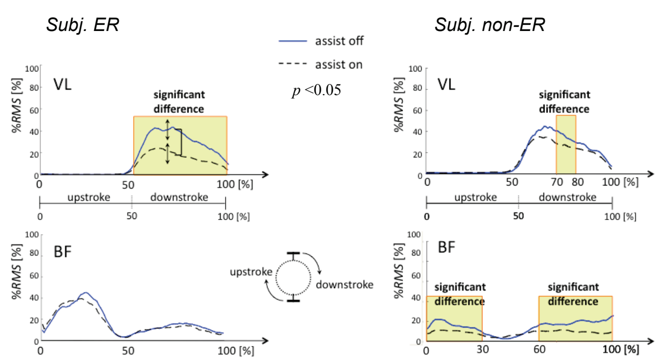


Figure 1. Synchronously averaged %RMS profiles in a late phase for VL and BF with (1:1) power assist-off (broken line) and –on (solid line) [11].

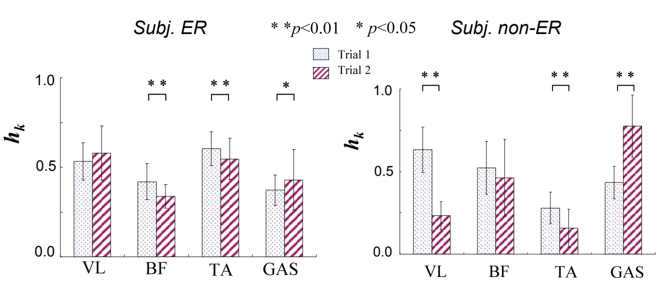


Figure 2. $\boldsymbol{h}_k$ at each muscle during cycling in the field

C. *Subjective muscle fatigue Supported by Objectively Measured Data during Cycling*

Figure 3 demonstrates the slope geography for the up-hill road section near the middle of our 20-min cycling circuit path. We used the personal customizing design process on two of the recruited subjects in the field experiments based on our noted conditions.

In this feasibility study, a polynomial approximation of the ARV time-series was used as the perceived physical fatigue because ARV was significant. Figure 4 shows a second order polynomial approximation of the ARV time-series. We preceded to use 5 to 15 s intervals for our predictions.

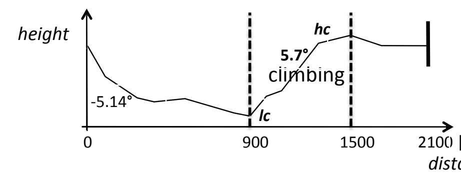
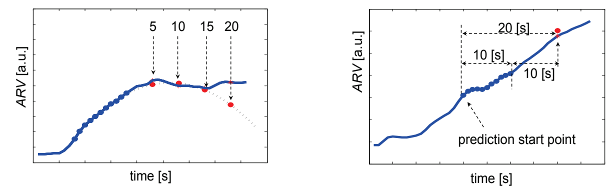


Figure 3. Slope geography in the circuit



(a) around lower corner in a early phase (b) around high corner in a late phase

Figure 4. Prediction of perceived muscle fatigue with ARV time-series; solid line and dot indicate estimated time-series and predicted ARV, respectively

IV. Discussion

A. *Muscle Synergies*

Since the knee-joint extension and flexion every 4 s was strictly periodical for the rugby members during the squat exercise, the maturity could be related to the small *s.d.* and small order of the synergy profile [19]. In addition, a high CC was considered to be like that associated with maturity and a further skill level. Since the BF muscle showed an explicitly significant difference in CC for the first and third synergies during a full squat, the muscle synergy pattern of BF could be an effectual evaluation index for better understanding the training skills; for the outdoor experiment, the muscle activation pattern showed a reciprocal contraction of the VL and BF for a routine cyclist in relation to the basic physical work capacity. The synergy profiles when comparing the muscle synergy profiles for skiing, pedaling, and squatting were related to the agonist/antagonist contraction types. [18]. The results could be evidence of maturity, which refers to the reciprocal contraction during muscle fatigue along with several skill-related motions [23].

Since the routine cycling participant had a strong pedaling force, the decrease in the ARV and $\boldsymbol{h}_k$ of VL could be caused by the power assist system. On the other hand, the decrease in the $\boldsymbol{h}_k$ for BF and not for VL happened for the non-routine cycling participant. The results could be related to the simultaneous pedaling torque required for sustaining the performance in each phase [19].

B. *Design of Biosignal-based Measurement and Control*

The participants in our previous field experiment [24], included eight healthy young male volunteers (23.8 ± 2.3 yrs), five middle age-aged female volunteers (44.2 ± 6.3 yrs), and four elderly male volunteers (61.3 ± 8.1 yrs). The muscle fatigue was assessed by focusing on the increase in ARV and decrease in MPF for a late segment [8], [11]. Moreover, the ARV profile for the crank angle was steady in the non-fatigue trial, while one for the elapsed time varied in a late phase. Thus, the muscle activity profiles in addition to the time-series of ensemble indices in a phase should be monitored. In addition, the *i*EMG ratio, that is the ratio of *i*EMG in each phase divided by one in the early phase, significantly increased in the fatiguing trials for the BF and TA muscles. Such variation was related to the individual fatigability, regardless of the age and gender of the related groups and torque profile for the EAB. We showed that at least five time-scales (stroke, segment, phase, section, and trial scales) were required to effectively customize the EAB for the fatigue assessment based on uphill road cycling using the SEMG related profiles, the %*i*EMG, and CC.

C. Subjective muscle fatigue Supported by Objectively Measured Data during Cycling

It should be noted that subjective data is also important for personally customizing a process because of the limitation of practically measured objective data. The biosignal-based workload control system for personally customizing a process should be developed based on a balance between the objective and subjective data, such as the RPE [7, 25]. Another choice for the perceived fatigue in relation to an objective physical index such as VO_{2max} or the cadence could be considered as an alternative [17]. On time feedback from the objectively measured physiological activity could be effective for supporting the subjective perceived fatigue [3].

V. Conclusion

We studied the effectiveness of subjectively presenting approaches that are based on the perceived fatigue prediction, using the idea of synergy and a multiple regression model for ubiquitously recognizing the status of functional activities instead of using objectively measured data, and proposed a power control system for electrically assisted bicycles (EABs). Synergy classified significantly changing muscles in relation to motion, that is, the muscles required for EAB cycling was found to be the VL and BF muscles, depending on a daily cycling routine or not. Moreover, modeling subjectively perceived fatigue by using objectively measured biosignals with multiple regression and polynomial approximation could be a potential approach for developing a personally customized control system of EABs. Finally, the experimental results showed that muscle activity profiles clarified the effect of a power assist system and the ongoing perceived physical fatigue could be predicted based on the time-series of the index, such as the ARV of SEMG.

References

[1] R. Paradiso, C. Belloc, G. Loriga, and N. Taccini, "Wearable healthcare systems, new frontiers of e-textile," Stud Health Technol Inform, vol. 117, pp. 9-16, 2005.

[2] E. Jovanov, A. Milenkovic, C. Otto, and P. C. de Groen, "A wireless body area network of intelligent motion sensors for computer assisted physical rehabilitation," *J Neuroengineering Rehabil,* vol. 2, p. 6, Mar 1, 2005.

[3] M. Sung, C. Marci, and A. Pentland, "Wearable feedback systems for rehabilitation," *J Neuroengineering Rehabil,* vol. 2, p. 17, Jun 29 2005.

[4] J. J. Chen, N. Y. Yu, D. G. Huang, B. T. Ann, and G. C. Chang, "Applying fuzzy logic to control cycling movement induced by functional electrical stimulation," *IEEE Trans Rehabil Eng,* vol. 5, pp. 158-69, Jun 1997.

[5] F. Chen, Y. Yu, Y. Ge, B. Wu, and J. Sun, "Basic Research on Power Assist Walking Leg Using Force/Velocity Control Strategies," *Conf Proc IEEE Info Acquisition,* pp. 701-6, 2006.

[6] A. Ueno, O. Miyashita, T. Yoshida, J. Yamamoto, and P. Lataire, "A wearable ECG-HR detector and its application to automatic assist-mode selection of an electrically assisted bicycle," *IEEE EMBC,* 2011.

[7] T. Kiryu, I. Sasaki, K. Shibai, and K. Tanaka, "Providing appropriate exercise levels for the elderly," *IEEE Eng Med Biol Mag,* vol. 20, pp. 116-24, Nov-Dec 2001.

[8] T. Kiryu and K. Yamashita, "A ubiquitous wearable unit for controlling muscular fatigue during cycling exercise sessions," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2007, pp. 4814-7, 2007.

[9] M. Simons, E. Van Es, and I. Hendriksen, "Electrically assisted cycling: a new mode for meeting physical activity guidelines?," *Med Sci Sports Exerc,* vol. 41, pp. 2097-102, Nov 2009.

[10] G. Sarre and R. Lepers, "Neuromuscular function during prolonged pedalling exercise at different cadences," *Acta Physiol Scand,* vol. 185, pp. 321-8, Dec 2005.

[11] T. Kiryu and J. Yamagata, "Relationships between muscle activity and autonomic regulation during cycling with a torque-assisted bicycle," *Conf Proc IEEE Eng Med Biol Soc,* vol. 1, pp. 2702-5, 2006.

[12] Y. Sankai, "Leading Edge of Cybernics: Robot Suit HAL," *IEEE SICE-ICASE,* 2006.

[13] N. A. Hakansson and M. L. Hull, "Muscle Stimulation Waveform Timing Patterns for Upper and Lower Leg Muscle Groups to Increase Muscular Endurance in Functional Electrical Stimulation Pedaling Using a Forward Dynamic Model," *IEEE TBME,* vol. 56, pp. 2263-2270, 2009.

[14] M. M. Mirbagheri, L. L. Ness, C. Patel, K. Quiney, and W. Z. Rymer, "The effects of Robotic-Assisted Locomotor training on spasticity and volitional control," *IEEE Int Conf Rehabil Robot,* vol. 2011, pp. 1-4, Jun 2011.

[15] G. Sarre and R. Lepers, "Cycling exercise and the determination of electromechanical delay," *J Electromyogr Kinesiol,* vol. 17, pp. 617-21, Oct 2007.

[16] K. J. Hunt, B. Stone, N.-O. Negard, T. Schauer, M. H. Fraser, A. J. Cathcart, C. Ferrario, S. A. Ward, and S. Grant, "Control strategies for integration of electric motor assist and functional electrical stimulation in paraplegic cycling: utility for exercise testing and mobile cycling," *IEEE TNSRH,* vol. 12, pp. 89-101, 2004.

[17] R. R. Bini, F. Diefenthaeler, and C. B. Mota, "Fatigue effects on the coordinative pattern during cycling: kinetics and kinematics evaluation," *J Electromyogr Kinesiol,* vol. 20, pp. 102-7, Feb 2010.

[18] T. Kiryu, T. Murayama, and Y. Ushiyama, "Influence of muscular fatigue on skiing performance during parallel turns," *Conf Proc IEEE Eng Med Biol Soc,* vol. 2011, pp. 8187-90, 2011.

[19] F. Hug, N. A. Turpin, A. Guevel, and S. Dorel, "Is interindividual variability of EMG patterns in trained cyclists related to different muscle synergies?," *J Appl Physiol,* vol. 108, pp. 1727-36, Jun 2010.

[20] R. Merletti, D. Farina, and M. Gazzoni, "The linear electrode array: a useful tool with many applications," *J Electromyogr Kinesiol,* vol. 13, pp. 37-47, Feb 2003.

[21] J. P. Clarys, K. Alewaeters, and E. Zinzen, "The influence of geographic variations on the muscular activity in selected sports movements," *J Electromyogr Kinesiol,* vol. 11, pp. 451-7, Dec 2001.

[22] G. A. Borg, "Perceived exertion: a note on "history" and methods," *Med Sci Sports,* vol. 5, pp. 90-3, Summer 1973.

[23] T. Kiryu and Y. Endo, "Evaluation on Training Types in Squat Exercise based on Muscle Synergies," *Conf Proc ISEK2012,* p. 355, 2012.

[24] T. Kiryu, H. Inada, and N. Sato, "Multi-Time Scale Evaluation of Prolonged Fatigue for Custmizing Electric Torque-Assisted Bicycles," *Conf Proc ISEK2010,* p. 308, 2010.

[25] E. Delattre, M. Garcin, L. Mille-Hamard, and V. Billat, "Objective and subjective analysis of the training content in young cyclists," *Appl Physiol Nutr Metab,* vol. 31, pp. 118-25, Apr 2006.