Acta Technica 62 No. 3A/2017, 225–234

ABS anti-fatigue training detection system in classification and recognition algorithm of inertia signal detection movement training based on naive Bayesian

Haidong Yang[1], Liyan Zhang[2,3]

Abstract. The human body sensor network is the application of the traditional wireless sensor network in the monitoring of the human body. It is a completely new human body monitoring technology, which provides remote medical service of human health. Inertial signal is a common method for human body sensor network to monitor the human body. In order to further expand the application range of the human body sensor network, this paper presents a method of human abdominal training monitoring based on inertial signal. The paper takes ABS bridging exercise as a case for the study, uses Naive Bayesian classifier to identify different bridging exercises, and achieves the supervision on the double bridging movement.

Key words. Inertial signals, ABS, double movement, anti-fatigue training.

1. Introduction

The abdominal muscles are important muscle tissues of the human body, and the main function of the abdominal muscles is to bound the human spine. As a result, it is difficult to provide strong constraints on the spine in the course of the exercise, easily leading to spinal damage or other accidental injuries [1, 2]. In the process of abdominal muscle strength training, it is necessary to monitor the training actions of abdominal muscles.

Monitoring of abdominal muscle training actions can provide direct feedback information of training effect for the patients and doctors, and help doctors to adjust the treatment plan in time according to the patient's recovery situation; moreover, it

[1]Northeastern University, Liaoning, 110819, China
[2]Shenyang Normal University, Liaoning, 110034, China
[3]Corresponding author; E-mail: prof_liyanzhang@163.com

can prevent the occurrence of overtraining. As a result, it is not only not conducive to rehabilitation treatment, but also affects the progress of rehabilitation of patients. For example, studies have shown that asymmetric upper body strength training will cause asymmetric compression on the disc of the human body, and long-term asymmetric strength training will easily lead to spinal injury [3].

The use of Electromyographic (EMG) for monitoring human abdominal training actions is the most commonly used method in clinical medicine and kinematics [4]. Through the calculation of average amplitude of ABS EMG signal in a period of time, we can obtain abdominal EMG activity. As an important indicator of the evaluation of ABS function, EMG activity is widely used in the existing studies [5]. The inertial sensor is one of the most commonly used devices to monitor the human body actions, and some studies have shown that there is a certain correlation between the inertial signal produced by the human motion and the EMG signal of the muscle [6]. This study uses the inertial measurement module to monitor human abdominal training action, and to replace EMG sign alto calculate EMG activity of ABS value by inertial signals, so as to realize the monitoring of the abdominal muscle training action.

2. Detection of ABS training action based on inertial signals

If it is proved that the same ABS training action will produce the similar EMG activity, then we can monitor the abdominal training action through sense network. We make use of inertial sensors to collect the inertial signals generated by the abdominal muscle training action, establish the relationship between the inertial signal and the EMG signal of the ABS, and calculate the EMG activity of abdominal muscle to achieve the monitoring of the abdominal muscle training.

2.1. Inertial signal acquisition device

This study uses the inertial measurement module (ADIS16405) produced by American Analog Device Inc for the acquisition of inertia signal produced in the abdominal training actions. ADIS16405 consists of three-axis accelerometer with a high precision and a high precision gyroscope. The maximum range of the acceleration sensor is $+\ 18\,\mathrm{g}$, the resolution is $3.33\,\mathrm{mg/LSB}$, the maximum range of gyroscope is $+\ 300\,\mathrm{deg/sec}$, and the resolution is $0.05\,\mathrm{deg}$ per second/LSB. In the experiment, ADIS16405 was installed on the data acquisition board (ADISUSBZ) produced by American Analog Device Inc.

2.2. Naive Bayes classifier

Figure 1 shows the processing of inertial signals in this study. First of all, we make use of Naive Bayesian classifier to identify different ABS actions by inertial signals, and establish different RBF neural networks according to the different recognition results. RBF neural network calculates the corresponding EMG signals through the inertial signals, and further calculate the EMG activity of abdominal muscles.

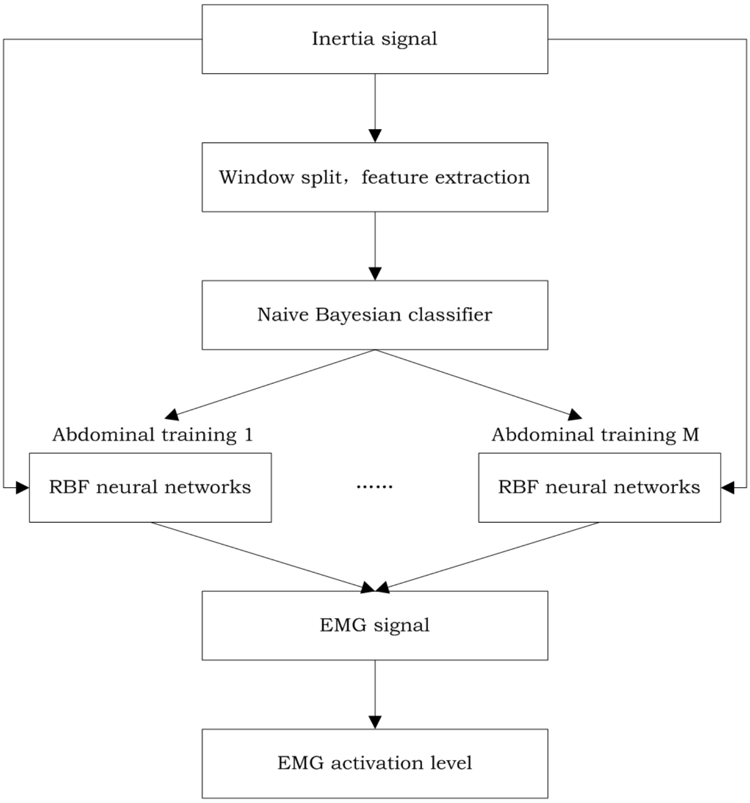


Fig. 1. Diagram of the processing of inertial signals

The Naive Bayes classifier is a classification algorithm based on the theory of the Bayes decision. In the classification process, it is assumed that the different dimensions in the feature space are statistically independent. Assuming that the unknown samples in the L-dimensional feature space are $X = (x_1, \cdots, x_L)$. Based on the independence assumption, X belongs to the probability of m-th category, which can be obtained by equation

$$p(X|\omega^m) = \prod_{l=1}^{L} p(x_l|\omega^m), \quad m = 1, \cdots, M. \tag{1}$$

The Naive Bayes classifier determines the classification category of unknown samples according to relation

$$\omega^* = \arg\max_m \left\{ p(\omega^m) \prod_{l=1}^{L} p(x_l|\omega^m) \right\}. \tag{2}$$

The advantage of the Naive Bayes classifier is that it only needs to estimate L

one-dimension probability density function $p\left(x_l\left|\omega^m\right.\right)$ in the training data, so that the algorithm training speed is rapid. In this study, the Parzen window method is used to estimate the probability density, and the Gauss function is used as the window function of the Parzen window. Assuming that there are N training samples belonging to the m class and x_l^n represents the lth component of the nth sample, then $p\left(x_l\left|\omega^m\right.\right)$ is estimated by the relation

$$p\left(x_l\left|\omega^m\right.\right) = \frac{1}{N}\sum_{n=2}^{N}\frac{1}{\sqrt{2\pi\sigma}}\left(-\frac{(x_l - x_l^n)}{2\sigma^2}\right). \tag{3}$$

3. Experimental design and experimental data acquisition

In order to verify the feasibility of the proposed method in the paper, the paper selects the double-bridge movement for the training of abdominal muscles. Double-bridge movement is the common strength training action of abdominal muscles, which can effectively stimulate the rectus abdominis, external oblique, internal oblique and multiple abdominal muscles parts. In the experiment, we simultaneously use EMG signals and inertial signals for monitoring abdominal EMG activity in double-bridge movement, and compare the difference of monitoring results of two kinds of monitoring methods. A total of 10 volunteers (6 males and 4 females) participated in the study, aged between 22–27 years old. None of the volunteers had a history of abdominal muscle, back muscle, and spinal disability. Before the experiment, all the volunteers were informed of the experiment objective, the experiment process and the risks of the experiment. 3 participants participated in the experiment, among them, two participants were responsible for the installation of the experimental equipment and the assistance of volunteers to complete the designated movement, and one participant was responsible for the receiving and sending of control collection system and data storage operation.

3.1. EMG signal acquisition of maximum voluntary contraction movement

In the standardized processing of EMG signal, it is necessary to implement the MVCs action to find the maximum EMG amplitude for each abdominal muscle. In this study, we selected 3 kinds of effective MVCs movements, the upper body forwarding, the upper body turning left and the upper turning right. Volunteers sat on the experimental platform, with his legs flat on the experimental platform; an experimenter tied the two legs, the volunteers back straight on the body of the other experimenter; the upper part of the body was bound by the experimenter. In the experiment, after the volunteers and members were in place, the volunteer back straight and forced forward bending of the body [7]. In this process, the experimenter strived to bound IS and make his body keep static, to help the volunteers stimulate the maximum EMG activity. And then, in this way, volunteers and experimenters completed the upper body turning left and the upper body turning right two MVCs movements. In the experiment, each MVC movement lasted for 3 seconds, and between the two adjacent MVCs, volunteers had 5 minutes to rest, to relax the abdominal muscles. The sampling frequency of EMG signal in the experiment is 1 kHz.

3.2. Inertia signal and EMG signal acquisition of double-bridge movement

The characteristics of double-bridge movement is that the actions are basically completed by the trunk. The upper limbs, lower limbs and other body parts still keep static. As a result, in the study, we need only an inertial measurement module worn in thoracic central to monitor the double-bridge movement. After completing all 3 groups of MVCs movements, the volunteers were given a 30-minute break. Then, the experimenter helped volunteers to wear the inertial measurement module in the thoracic central position. Volunteers conducted the double movement in 4 different postures, including the supine and prone double-bridge movement, lying on double-bridge movement, the left side lying double-bridge movement, and the right side lying double-bridge movement. In the experiment, each double-bridge movement lasted for 20 seconds, while volunteers needed to complete 6–7 action cycles. Each of the volunteers repeated a double-bridge movement for 5 times, and two adjacent double-bridge movement had the interval of 10 minutes. In the experiment, the sampling frequency of the EMG signal is 1000 Hz, and the sampling frequency of inertial signals is 435 Hz.

4. Analysis of experimental results

The inertial signals acquired in double-bridge are conducted with smooth processing of moving mean window with length of 100 m sec, and then we can get the inertial signals with sampling frequency of 10 Hz.

4.1. Classification accuracy of Naive Bayes classifier

1) Data preprocessing

The duration of each double-bridge movement in the experiment was 20 seconds, including 6–7 operation cycles, so the sliding window segmentation length is 4 seconds, making each observation window contain a complete action cycle. The characteristics of the inertial signals extracted from the observation window are mean and variance, and each feature is 12-dimensional.

2) Validation method

In this paper, the remaining-one method is used to verify the classification accuracy of the Naive Bayes classification. In 10 volunteers, choose the experimental data of a volunteer as the test data, and the experimental data of the other 9 volunteers as the training data. The verification process is repeated 10 times. Take the experimental data of different volunteers selected each time as test data, and the final results of the verification take the average value of the verification process for 10 times.

3) Experimental results

In the experiment, the recognition accuracy of all the 4 kinds of double-bridge movements using the Naive Bayesian classifier all reached 100 %. The reason for the high accuracy is that the body showed different postures in the 4 kinds of double-bridge movements, and it can easily distinguish by the acceleration signals. Figure 2 shows the acceleration signals of two kinds of actions, lying on the left and lying on the right (unit for the gravity accelerating). The body lying on the left double-bridge movement, axis acceleration signal value gets close to 1, while lying on the right double-bridge movement, the axis y acceleration signal is close to -1.

4.2. Calculation of the EMG activity of abdominal muscles by using the Radial basis function neural network (RBF)

1) Data preprocessing

For the EMG signal collected in the experiment, first of all, the RMS smooth processing and standardized processing are carried out.

2) Validation method

In the experiment, we established 4 RBF neural networks, and each network corresponds to a double-bridge movement. In the experiment, each volunteer repeated a double-bridge movement for 5 times. The inertia signal and EMG signal of the former 4 times double-bridge as the training data, and the test data is the inertial signal and EMG signal of fifth time double-bridge movement.

3) Experimental results

As shown in Fig. 4, it is the mean and standard of myoelectric activity, external oblique, EMG activity of internal oblique in four different double-bridge movement. From Fig. 4, we found that myoelectric activity of EMG activity was obtained by calculating the inertial signal and EMG activity obtained by EMG signal is very similar. The average calculation error of the 8 blocks of the abdominal musclesin the 4 kinds of double-bridge movement were 2.56 (MVC %), 2.99 (MVC %), 1.73 (MVC %) and 3.13 (MVC %). The experimental results showed that for the double-bridge movement, we can use inertial sensor to replace EMG acquisition equipment to realize the supervision of ABS training actions.

The mean errors in bridge motion were 2.56 (MVC %), 2.99 MVC %), 1.73 MVC %, and 3.31 MVC %). The experimental results show that inertial sensors can be used instead of EMG acquisition equipment to supervise the training of abdominal muscles.

Experimental results show that different dual bridge motions can be accurately identified by inertial signals. At the same time, the EMG activity of the abdominal muscles computed by inertial signals can be well matched with the level of EMG activation calculated by the EMG signal. It is worth emphasizing that the effectiveness of the approach presented in this study is currently limited to dual bridge exercise. For the feasibility of other abdominal exercises, a large number of experimental verification and calculation methods are needed. For example, abdominal exercises performed in Rutkowska-Kucharsk's study required the upper limbs, lower limbs and trunk to work together. If inertial sensors are used to monitor this train-

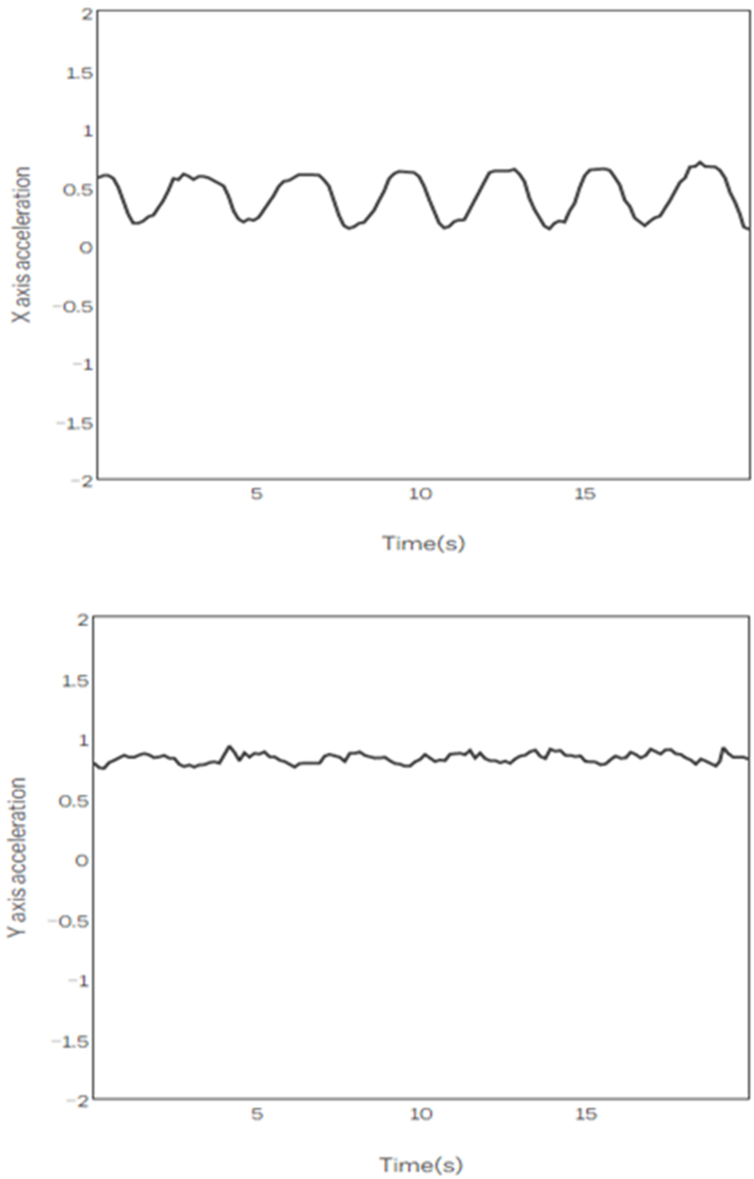
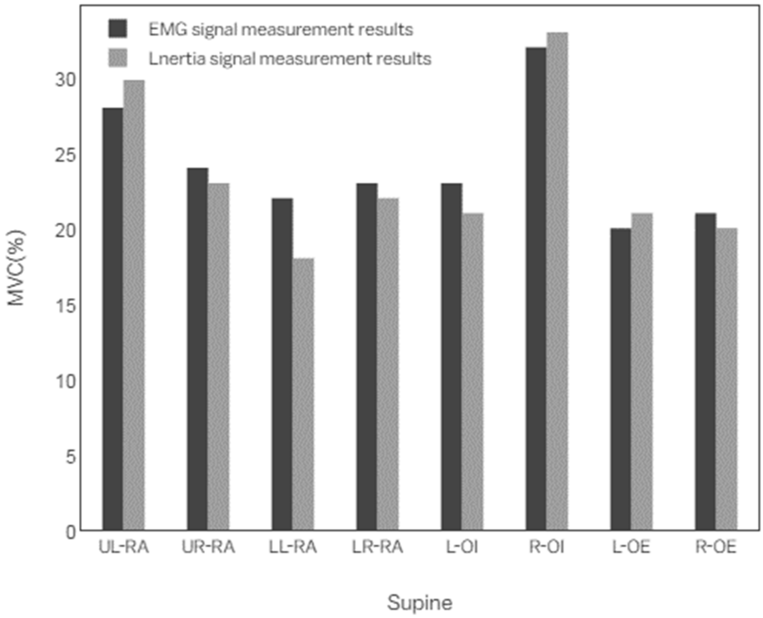
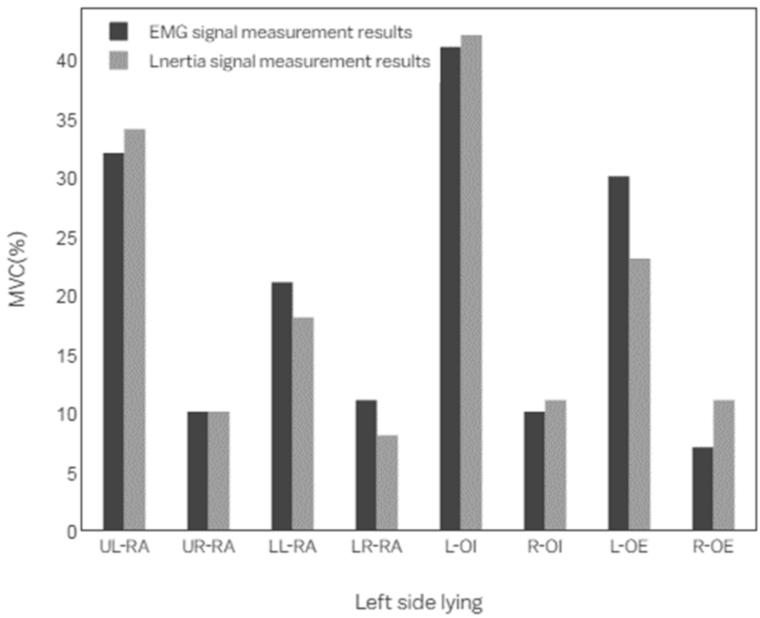


Fig. 2. Acceleration signal of lying on the left double-bridge movement

ing, a number of sensor nodes needs to be worn on the arm, thigh and upper body. Therefore, it is necessary to adjust the corresponding calculation process. In addition, some abdominal training exercises use additional load (such as dumbbells) to enhance the abdominal muscle stimulation intensity. The weight of the load does not have a direct effect on the inertial signal, but it can cause different EMG activity. For one of these abdominal exercises, external factors need to be incorporated into the calculation.





5. Conclusion

In this paper, taking double-bridge movement as a case study, we analyzed the feasibility of using inertial signal for monitoring abdominal training action. We

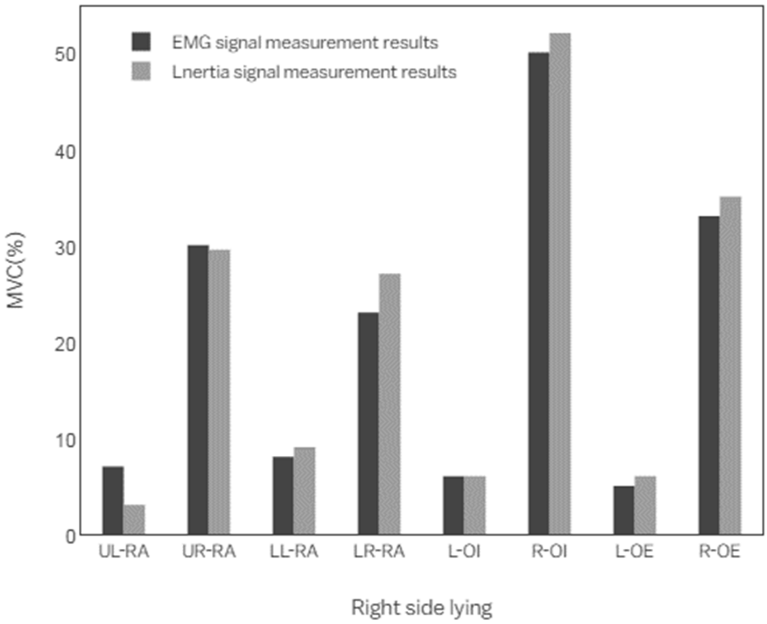


Fig. 3. Mean and standard of rectus abdominis (up), external oblique (middle) and EMG activity of internal oblique (bottom) in 4 kinds of different double-bridge movements

studied and established the Naive Bayes classifier to identify different double-bridge movements by inertial signals. The experimental results showed that the Naive Bayes classifier achieved high recognition accuracy. In addition, the EMG activity obtained through the inertial signal is similar to that obtained through using EMG signal. The experimental results showed that for the double-bridge movement, we can fully use inertial sensors to replace EMG acquisition equipment to realize the supervision of abdominal training action.

References

[1] [P. Kjaer, C. Leboeuf-Yde, L. Korsholm, J. S. Sorensen ,T. Bendix: *Magnetic resonance imaging and low back pain in adults: a diagnostic imaging study of 40-year-old men and women.* Spine *30* (2005), No. 10, 1173-1180.

[2] K. Freburger, G. M. Holmes, R. P. Agans, A. M. Jackman, J. D. Darter, A. S. Wallace, L. D. Castel, W. D. Kalsbeek, T. S. Carey: *The rising prevalence of chronic low back pain.* Archives of Internal Medicine *169* (2009), No. 3, 251–258.

[3] J. A. Hides, W. R. Stanton, M. Freke, S. Wilson, S. McMahon, C. A. Richardson: *MRI study of the size, symmetry and function of the trunk muscles among elite cricketers with and without low back pain.* British Journal of Sports Medicine *42* (2008), No. 10, 809–813.

[4] M. Monfort-Pañego, F. J. Vera-García, D. Sánchez-Zuriaga, M. A. Sarti-

Martínez: *Electromyographic studies in abdominal exercises: A literature synthesis.* Journal of Manipulative & Physiological Therapeutics *32* (2009), No. 3, 232–244.

[5] P. W. Marshall, I. Desai: *Electromyographic analysis of upper body, lower body, and abdominal muscles during advanced Swiss ball exercises.* Journal of Strength & Conditioning Research *24* (2010), No. 6, 1537–1545.

[6] H. D. Cho, J. H. Lee, J. H. Jeong, J. Y. Kim, S. T. Yee, S. K. Park, M. K. Lee, K. I. Seo: *Production of novel vinegar having antioxidant and anti-fatigue activities from Salicornia herbacea L.* Journal of the Science of Food and Agriculture *96* (2016), No. 4, 1085–1092.

[7] B. Yang, Y. Lei, B. Yan: *Distributed multi-human location algorithm using naive Bayes classifier for a binary pyroelectric infrared sensor tracking system.* IEEE Sensors Journal *16* (2016), No. 1, 216–223.

Received May 7, 2017