Muscles Cooperation Analysis Using Akaike Information Criteria for Anterior Cruciate Ligament Injury Prevention

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***Abstract*— In this paper, we propose the analysis method for finding out the similarity of the muscle force patterns to mine the risk factor of the anterior cruciate ligament (ACL) injury. Akaike information criteria (AIC) under the assumption of the auto-regression model is adapted to analyze the similarities of muscle force patterns in time-series. The difference of AIC values between 2 muscles is considered to be the distance between 2 muscle force patterns and the dexterity of the maneuver is expected to be discussed. We measured drop vertical jump (DVJ) and use the data around the contact timing of whom hadn't had ACL injury experiments. The results showed that we could successfully calculate AIC distance according to the similarity of the time-series data pattern and it can be useful to discuss one's dexterity of controlling body maneuvers soon after contact timing of DVJ motion.**

I. Introduction

A. Background

Injuries during sports activities (sports injury) affect an athlete's performance not only at the time of being injuries but also after his/her recovery. To develop a training method for preventing sports injuries in advance, knowing the specificities of the athlete's body maneuvers is desirable for better instruction for improving their maneuvers.

However, what is the ideal maneuvers during athletic events, and what is the dangerous maneuvers or risk factors that cause athletes' injuries are not enough clarified quantitatively yet. Authors[1][2] have worked on the assessments of the risk of the anterior cruciate ligament (ACL) injuries by the measurement and analysis of the physical motions during the drop vertical jump (DVJ) motions[3], which is commonly used as a screening test for ACL injury risk assessment. As far, analysis of the DVJ motions mainly on joint angles at a certain timing during the jump. However, the recent development of the measurement tools enables us to capture whole a motion easily and to acquire much abundant information. Thus, new analysis frameworks such as time-series analysis or muscle force analysis are required to deeply know athletic maneuvers.

*This work was supported by JSPS KAKENHI for JSPS Fellows (18J10752) and Grant-in-Aid for challenging Exploratory Research (Grant Number 17H06291).

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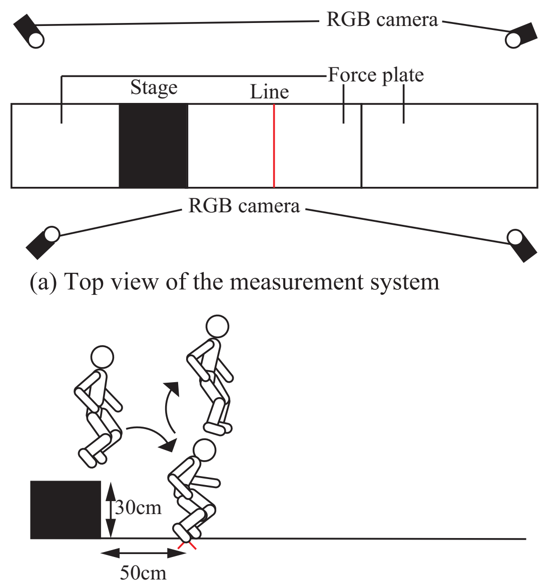

(a) Top view of the measurement system

(b) Side view of the measurement system

Fig. 1. The measurement system and the outline of DVJ motion. (a) The top-view of the measurement system. Three force plates are on the ground, and the stage is put on one of the force plates. Four RGB cameras were surround of the force plate and the stage. The line are illustrated 50cm-former of the stage. (b) The side-view of the measurement system. The outline of the DVJ motion are also illustrated. The participant is asked to stand on the stage and to jump from the stage targeting the line illustrated 50cm-former of them. Soon after touching the ground, the participant try to jump as high as they can.

The muscle activities at the contact time are regarded to be generated by the changing in time through the cooperates among muscles, so we think that the analysis of the cooperates among the muscles will bring us more detailed risk assessment of the ACL injuries at the timing of getting impact from the ground.

Akaike's information criterion (AIC)[4] calculates similarities of distributions between 2 different models. Akai et al.[5] utilizes AIC to cluster questionnaire items as comparing answer patterns of a questionnaire. If we regard the muscle activation pattern as one specific distribution model, we can calculate the similarities as same as the answer patterns of a questionnaire using AIC.

B. Purpose of this research

This research is aimed at mining the body maneuvers that cause ACL injuries through analysis of cooperations among muscles during DVJ motion. We propose a time-series analysis method that regards each muscle time-series data as a series of measurement values and estimates the similarities among the data distributions by calculating AIC differences.

II. AIC-BASED ANALYSIS FOR TIME-SERIES DATA

A. Akaike Information Criteria[5]

AIC is one of indices that calculates the similarities of the distributions using mutual information. Using the log-likelihood l and the degree of freedom k, AIC is expressed as $-2(l-k)$. The log-likelihood l can be calculated by the maximum likelihood estimation.

B. Time-series data pattern analysis by AIC

AIC had been introduced to design questionnaires[5] in the risk assessment field. This method checks the cooccurent of answers of items in a questionnaire and clusters the items by their similarities. Questionnaires for assessments, e.g., psychological effects after ACL injuries[6] and the locomotive disorders mainly of elderly people[7][8] had been designed. [6][7][8] had adapted the method described in the previous subsection to the categorical data, so the multinominal distribution model was used. However, since our data is time-series data, we need to modify the suitable distribution model. The difference of the model can be regarded as the difference of perspectives we focus on. The multinominal model is focusing on the coocurrence of the data, whereas we'd like to focus on the synchronisity of the data.

Let assume that the physical motion data $\mathbf{x}(t)$ at the specific time point t is determined by previous physical motion data measured during the certain time span, then $\mathbf{x}(t)$ can be expressed as follows based on the autoregressive model:

$$\mathbf{x}(T) = \sum_{t=1}^{M} a_t x_{T-t} + \varepsilon_t, \qquad (1)$$

where the number of weight parameters (the number of samples that we use for the autoregression as the previous data) M, the elements of weight vectors a_t, and the number of samples of the physical motion data N. We assumed that ε_t is generated according to the normal distribution of which the mean is 0 and the variance σ^2. We estimate the weight a_t for the physical motion data and noise ε_t by the maximum likelihood estimation and use them for AIC calculations.

The maximum log-likelihood can be expressed as

$$l = \log p(\hat{\mathbf{a}}, \hat{\sigma^2}) = -\frac{N-M}{2}\log(2\pi\hat{\sigma^2}) - \frac{N-M}{2}, \qquad (2)$$

where

$$\hat{\sigma}^2 = \frac{1}{N-M}\sum_{t=1}^{N-M}(x_t - \sum_{j=1}^{M}\hat{a}_j x_{t-j})^2. \qquad (3)$$

Then, $F(\mathbf{x}_0(T))$ and $F(\mathbf{x}_1(T))$; AIC for 2 time-series physical motion data at the time T, can be expressed as follows:

$$\begin{cases} F(\mathbf{x}_0(T)) = l_0 - M_0 \\ F(\mathbf{x}_1(T)) = l_1 - M_1 \end{cases}$$

In this paper, we treat the human physical motion data, so the number of samples using for the autoregression M is determined as referring to the neural reflexion velocities of humans, i.e., 100ms. Also, $M_0 = M_1$. Then, calculating $\|F(\mathbf{x}_0(T)) - F(\mathbf{x}_1(T))\|$, we can acquire the difference of the AIC between $\mathbf{x}_0(T)$ and $\mathbf{x}_1(T)$. Smaller this difference, we can consider that these 2 time-series data are more similar.

III. PHYSICAL DVJ MOTION DATA MEASUREMENT

A. DVJ motion measurement

We conducted DVJ motion measurements for sport players who are in their 10-20s and belong to amateur teams. The measurement method is as follows[1]: The participant jumped up from the 30cm-height stage pointing to the line shown 50cm-former, and soon after they reached the showing line jump vertically as high as possible they can. There were 3 trials for each participant; the participants were asked to contact the ground by their both feet, their right foot, their left foot in each trial. The physical motion data were collected by force plate (1000 fps) and the video motion capture system (VMocap)[9]. VMocap enables us to capture 3D joint positions from images taken by multiple RGB cameras and can calculate inverse kinematics/dynamics from the data, so we don't need to attach any kind of sensors on participants' bodies and easily analyze natural motions. Image data were captured in 30 fps from 4 RGB cameras and joint positions were estimated from them. Using the estimated joint positions, we can calculate inverse kinematics and inverse dynamics of the musculoskeletal model[10]. Throughout this VMocap flow, we can calculate the estimated muscle force without any sensors attached to the participants' bodies. We defined the timing when the participant toe/heel touches the ground at the first as IC (Initial Contact) and the timing the participant's knee was bented maximally as MFK (Maximum Flexion of Knee), and the timing when the participant jumps up soon after IC as TO (Toe Off), and use the muscle force data from IC to MFK / MFK to TO. Each timing was detected manually from the joint marker positions reconstructed by the video motion capture system. The measurement system and the outline of DVJ motion are shown on Fig. 1. The experimental procedures were approved by the ethical committee at the University of Tokyo.

B. Time-series physical motion data for analysis

We selected 17-year-old female participant who had not have experiences of ACL injuries. The right lower leg muscle force during one's trial of the right leg jump and the left lower leg muscle force during one's trial of the left leg jump were analyzed. The number of frames using for the analysis (the time between IC to MFK / MFK to TO), i.e., N in Eq.

TABLE I

THE CORRESPONDING TABLE OF MUSCLES (PART OF THE BODY, ID, NAME, NUM. OF LINKS)

Part of the body	Muscle ID	Muscle name	Number of wires
Trunk	1	Gluteus Maximus	6
	2	Gluteus Medius	3
	3	Psoas Major	9
(around pelvis)	4	Iliacus	2
	5	Tensor Fasciae Latae	1
Thigh	6	Vastus Intermedius	1
	7	Vastus Lateralis	1
	8	Vastus Medialis	1
	9	Rectus Femoris	1
	10	Sartorius	1
	11	Semimembranosus	1
	12	Semitendinosus	1
	13	Grachilis	1
	14	Adductor Longus	1
	15	Adductor Magnus	3
	16	Biceps Femoris	2
Calf	17	Gastrocnemius	2
	18	Soleus	2

(2) is 11 frames (366 ms) /12 frames (400 ms) for the right jump, and 9 frames (300 ms) /12 frames (400 ms) for the left jump. The weight parameter M is set as 4 frames (120 ms), which is estimated as the time for the flexions.

Our musculoskeletal model[10] is a whole-body model, but in this paper, we analyzed only the muscles of the lower limbs for ACL injury risk assessment. The muscles used for the analysis were 18 muscles expressed as 39 wires in the system. The 18 muscles were; Gluteus Maximus, Gluteus Medius, Psoas Major, Iliacus, Tensor Fasciae Latae, Vastus Intermedius, Vastus Lateralis, Vastus Medialis, Rectus Femoris, Sartorius, Semimembranosus, Semitendinosus, Grachilis, Adductor Longus, Adductor Magnus, Biceps Femoris, Gastrocnemius, Soleus. The correspondence table between muscle names and the number of wires in the system are shown on Tab. I. In this paper, we calculate muscle forces as the sum of the force of each wire, and calculate AIC for the 18 muscles (39 wires) of the right lower limb during the right jump and the 18 muscles (39 wires) of the left lower limb during the left jump, and regarded the difference of AIC as the distance between 2 muscles distributions, then tried to visualize them as the distance matrix.

IV. MUSCLE COOPERATIONS ANALYSIS BY AIC

A. Results of distance calculations

Fig. 2 show the distance matrix for each wire. The color of the $(i,\ j)$ grid indicates the degree of the AIC difference for the combination of muscles of ID i and ID j. Each ID on the row/col in the Figure corresponds with the ID for each muscle assigned in Tab. I. The darker color indicates the smaller AIC difference, i.e., if the grid $(i,\ j)$ showed the darker color, the muscle i and j shows a similar trends in time-series data from IC to MFK (the left side) and from MFK to TO (the right side) of the DVJ trial. The upper figures are the results for the right leg jump data, and the lower figures are for the left leg jump data. The AIC difference of one link ($i = j$) will be 0 because they are the totally same data.

TABLE II

THE KNEE VALGUS ANGLES AT IC, MFK, TO

		IC	MFK	TO
Knee valgus	Right	177.9°	159.3°	174.6°
	Left	171.3°	169.8°	170.5°

B. Similarities between muscle activity patterns

Since AIC calculate similarities of distributions of the data, smaller AIC means that similar muscle activity patterns between 2 muscles. So, if the (i, j) grid in Fig. 2 darker, the muscle activity pattern of muscle i and muscle j are similar. In other words, the muscle i and the muscle j are synchronizing during the duration we focused on and calculated AIC difference between them. From above discussion, it can be said that if there is a row that is mainly in darker color, the corresponding muscle activates syncronizing with many muscles, whereas if there is a row that is mainly in lighter color, the corresponding muscle activates independently.

Seeing the figures, rows and columns that are corresponded with the combination among Vastus Intermedius, Vastus Lateralis, and Vastus Medialis showed black color in the figures of IC to MFK during both the right leg jump. From the figure of MFK to TO during the left leg jump, adding to the combination among these 3 muscles, Rectus Femoris also showed a small AIC difference between Vastus Intermedius, Vastus Lateralis, and Vastus Medialis, each whereas the figure of MFK to TO during the right leg jump only showed the combination between Vastus Lateralis and Vastus Medialis. These four muscles are called as the quadriceps and work as the extensor muscle of the lower limb. Thus, we can say that we could extract similarities of the data pattern by the proposed method.

Comparing Fig. 2 (a) and (b), muscle activation patterns drasticaly change but the changing patterns were opposite between the right leg (Fig. 2 (a)) and the left leg (Fig. 2 (b)). Since the knee valgus angles of the right/left leg at IC, MFK, TO differs as shown on Tab. II, we compared with the figures of right/leg muscles, the left leg showed wider range of distances during IC to MFK whereas the right leg showed the same tendency during MFK to TO. It indicates that the muscle cooperation patterns in time series differs with the side of the legs.

V. CONCLUSION

To proceed ACL injury prevention researches, we proposed a muscle cooperation analysis method based on network analysis using AIC on the time-series physical motion data during DVJ motion. In this paper, to adapt AIC calculation to the time-series data, the autoregression model is assumed and the log-likelihood was calculated. Also, the evaluation method for the distribution similarity among time-series data by taking the difference between the AIC of the muscle forces was proposed. We successfully calculated AIC and visualized the combinations of muscle links referring to their AIC differences.

The limitation of this research is the shortage of participants. In this paper, we'd like to introduce our new method to analyze the similarities of muscle activate patterns,

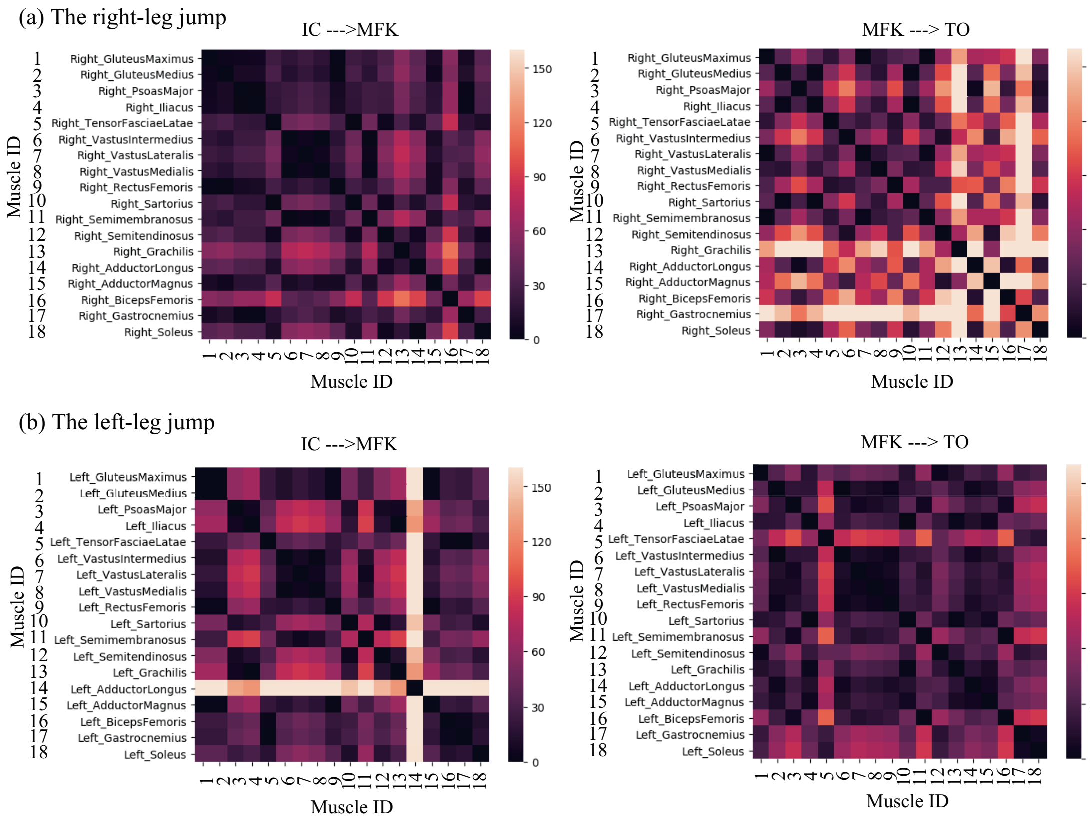

Fig. 2. The visualized distance matrix between each pair of muscles. Each ID on the row/col in the Figure corresponds with the ID for each muscle assigned in Tab. I. The darker color indicates that the shorter distance (the smaller AIC) between two muscles. (a) The upper side subfigure indicates the distance matrix of the right leg muscle during the right leg DVJ. (b) The bottom side subfigure indicates the distance matrix of the left leg muscle during the left leg DVJ. For both (a) and (b) subfigures, the left side figure is the result for the data during IC to MFK, the right side figure is the result for the data during MFK to TO.

so we select only 1 participant and discussed the validity of our method. For further research, we are planning to analyze many more participants who have/do not have the experiences of ACL injuries and compare the AIC distances among those participants. Also, this method has the limitation that muscles that have similar properties (i.e., the response characteristics) tend to have similar AIC values because the AR model estimates a kind of transfer function of muscles. However, the duration of the DVJ motion we analyzed were long enough and participants are expected to realize their voluntary motion during IC to TO for the preparation of the next jump, we think that our method can also analyze taking into account of this voluntary motion.

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