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Examination of a muscular activity estimation model using a Bayesian network for the influence of an ankle foot orthosis

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Abstract. **In the present paper, we examine the appropriateness of a new model to examine the activity of the foot in gait. We developed an estimation model for foot-ankle muscular activity in the design of an ankle-foot orthosis by means of a statistical method. We chose three muscles for measuring muscular activity and built a Bayesian network model [1] to confirm the appropriateness of the estimation model. We experimentally examined the normal gait of a non-disabled subject. We measured the muscular activity of the lower foot muscles using electromyography, the joint angles, and the pressure on each part of the sole. From these data, we obtained the causal relationship at every 10% level for these factors and built models for the stance phase, control term, and propulsive term. Our model has three advantages. First, it can express the influences that change during gait because we use 10% level nodes for each factor. Second, it can express the influences of factors that differ for low and high muscular-activity levels. Third, we created divided models that are able to reflect the actual features of gait. In evaluating the new model, we confirmed it is able to estimate all muscular activity level with an accuracy of over 90%.**

I. INTRODUCTION

The rapidly increasing number of individuals with leg disabilities caused by such conditions as cerebrovascular disease and spinal cord injury is a serious problem. Patients with these disabilities need to start rehabilitation at an early stage after injury. As part of the walking assistance and rehabilitation for such disabled individuals, foot orthosis plays an important role in both the convalescent and chronic phases. The type of foot orthosis depends on the severity of the disorder (Fig. 1). Using an ankle-foot orthosis (AFO) enables patients to make an earlier resumption of their normal social activities and is helpful for rehabilitation. However, if suitable training is not performed or the proper orthosis not chosen, the muscular power of patients seriously weakens, the range of motion (ROM) of their joints diminishes, and they lose the ability to time the movement of their muscles in gait. Consequently, patients who do not receive appropriate rehabilitation may depend on the AFO for the rest of their lives, which is clearly not an optimal situation for most individuals. In addition, this results in increased medical costs for society as a whole. Further, limiting the flexibility of the lower limbs has a negative influence on the information input to the central nervous system.[2] Therefore, we believe that an AFO should attempt to correct only the minimum number of necessary joints because this will help prevent the patient being reliant on the AFO longer than required.

Fig. 1 Variety of lower-leg orthoses

In some recent large projects, new orthoses using a mechanical engineering approach have been developed, for example, the Gait Solution, which uses a hydraulic brake at the ankle joint [3], and an orthosis with a ferrofluid brake at the ankle [4] (Fig. 2). These new orthoses prevent drop foot and stumbling. And by correcting the minimum necessary number of joints, they allow more natural walking and natural use of muscles. However, the problem with these projects is the excessive cost and time (more than 10 years) spent developing the new orthoses: these factors are clearly not conducive to creating effective new devices. One solution to this problem is to estimate the effectiveness of a proposed new AFO before development gets under way. This would be helpful in reducing or eliminating the risk of failure in final stages of the project.

Fig. 2 New lower-leg orthoses [3][4]

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The objective of the present study was to develop a foot-ankle muscular model for designing an AFO. The model had to consider all factors of gait, for example, bones, reflex movements, and joint angles. In this paper, we examine the appropriateness of our new model by comparing the model with the actual activity of the foot during gait.

Some research on the 3D kinematics of a foot model has been conducted. Delp et al. created OpenSim, which simulates movements of the whole body [5]; it was developed as an open source and so has been used by many researchers.

Kim et al. created a nine-segment foot model with three dimensions for normal walking [6]. Takashima et al. performed a dynamic model analysis of the human foot [7]; the analysis placed particular emphasis on the movements of the arch joint and one metacarpophalangeal (MP) joint. However, these models require actual measurements during particular movements and simplify or ignore some factors. Our proposed model can evaluate muscle activity using the established statistical method of Bayesian network estimation. This technique can help create a graphical model that expresses a set of random variables and conditional dependencies via a directed acyclic graph. [1] This model would appear to be indispensable for making improved effective foot orthoses, and it can almost certainly be applied to other fields of orthosis or rehabilitation.

II. APPROACH

We built three muscular-activity estimation models using a Bayesian network to estimate the influence of the orthosis on the muscles of the lower limb. The first estimation model was the stance phase; the second was the control term (0%–20% gait cycle [GC]); and the third was the propulsive term (20%–50% GC; Fig. 3). We used these three estimation models to reflect the different roles of muscular activity between the points of almost heel contact and almost toe-off. The control term is the time needed to regain the trunk balance lost in the swing phase, and the propulsive term is the time when an impelling force is generated.

The Bayesian network builds a causation model from the joint probability of many phenomena to estimate the probability of a desired outcome under certain conditions. As an example in another field, Bayesian estimation can distinguish spam e-mails by filtering combinations of various words in messages [8].

The following three reasons further illustrate the benefits of using a Bayesian network in the present study:

a) It can build a statistical model that reflects factors omitted or oversimplified in a physical model;

b) The Bayesian network can build the model in advance, and it is not necessary to modify it every time a condition changes;

c) It can estimate the result from a cause in addition to estimating the cause from a result.

In building the foot muscular activity model for a lower-foot orthosis, we divided the electromyography (EMG) of the muscles, the angle of each joint, and the sole pressure on each part into 10 levels, as shown in Fig. 4. We used these to determine the threshold and to make nodes for the Bayesian network. This method can distinguish the influences caused by different conditions of some parameters into high or low influences.

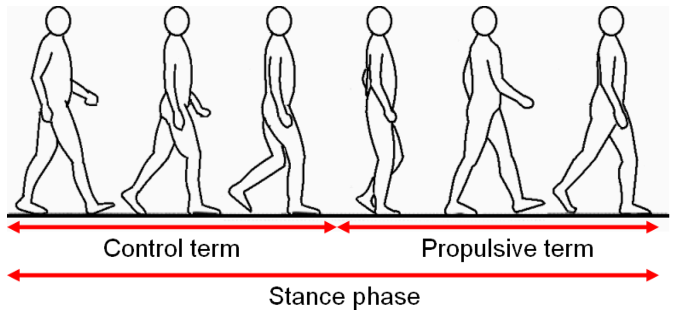

Fig. 3 Dividing the cycle of gait

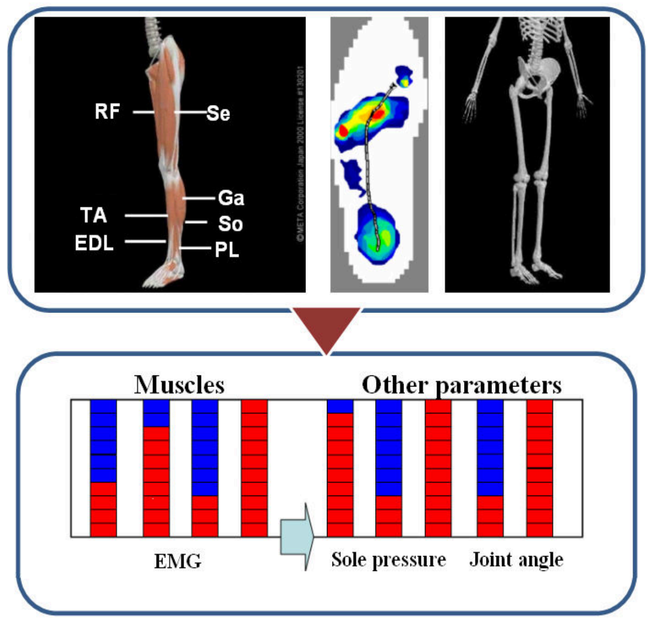

Fig. 4 Nodes of the Bayesian network

RF, rectus femoris muscle; Se, semitendinosus muscle; TA, tibialis anterior muscle; Ga, gastrocnemius muscle; So, soleus muscle; PL, peroneus longus muscle; EDL, extensor digitorum longus muscle

III. MEASUREMENT OF MUSCLE ACTIVITY AND MOTION OF THE FOOT DURING WALKING

The purpose of measuring muscle activity and motion of the foot during walking was to confirm the effectiveness of the muscular activity estimation method using a Bayesian network model. The subject used in the present study was a non-disabled male in his twenties. In the experiment, the subject walked on a track without shoes or an AFO (Fig. 5).

We measured the normal gait to obtain the following measurements:

EMG: tibialis anterior muscle (TA); peroneus longus muscle (PL); gastrocnemius muscle (Ga).
Angle: knee, ankle, metatarsophalangeal joint (big toe, third toe, fifth toe)
Sole pressure: ① big toe; ② fifth toe; ③ thenar eminence; ④ hypothenar eminence; ⑤ outside metatarsus; ⑥ calcaneus (Fig. 6)
Other: Floor reaction force.

The MP joint is the root joint of the toes and is rarely used to measure gait. Since we previously investigated the influence of the AFO on the MP joint [9], in the present study we wanted to establish the relevance of the toes to the EMG. In analyzing the sole pressure while walking with and without the AFO, it was found that the load was lightly applied to the forefoot when the AFO was worn. This implies that the load was not applied to the MP joint. After several years of AFO use, the lack of a load applied to the MP joint can have a negative influence on a patient's recovery. Thus, it is necessary to measure the angle of the MP joint, and we measured the sole pressure of the toes in addition to the angle of the MP joint.

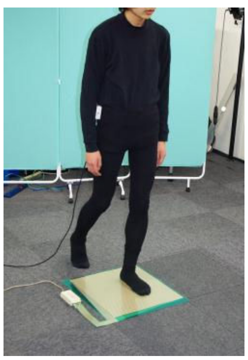

Fig. 5 Gait measurement

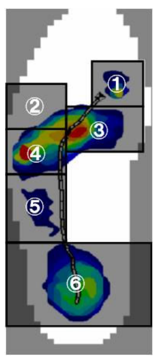

Fig. 6 Divisions of the sole

IV. Building Method of the Bayesian Network Model

We built an estimation model of the foot's muscular activity during gait from the data listed in the previous section, and we divided the measurement data by the floor reaction force. Figure 11 shows the direction of motion of the floor reaction force. In the control term, the body velocity slows down to gain balance. Therefore, the control term is negative until the body gains balance. In propulsive terms, humans apply force to the floor and the body accelerates. Thus, the propulsive term is always positive.

We used data from all our trials to construct the Bayesian network; we determined the maximum of each measured value at the maximum activity level and the minimum of each measured value at the minimum activity level during gait. The data were divided into 10 levels between the maximum and minimum activity levels, and these levels were used as the node thresholds. We chose the K2 algorithm [10] for the search procedure. The K2 algorithm is a variety of greedy algorithm, and the technique involves adding a node that determines the parent node candidate; this can become a parent node to all the nodes, which are added one by one to the parent node. From each combination of nodes we choose one combination that has most little information criterion. Information criterion is calculated as follows:

$$p(X_i \mid pa(X_i)) = \prod_{j=1}^{q_i} \frac{(r_i-1)!}{(N_{ij}+r_i-1)!} \prod_{k=0}^{r_i-1} N_{ijk}! \qquad (1)$$

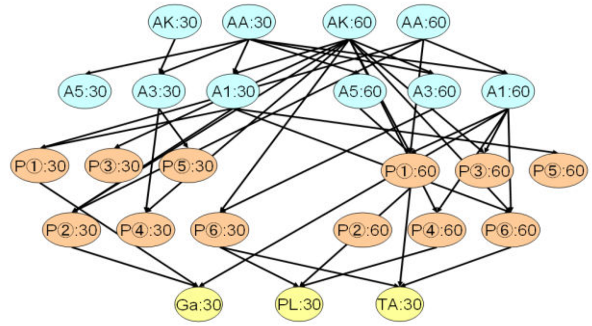

Fig. 7 A part of Bayesian network
AK：Angle of knee AA: Angle of ankle
A5,A3,A1: Angle of each MP joint
P1-P6: Pressure on each part of sole

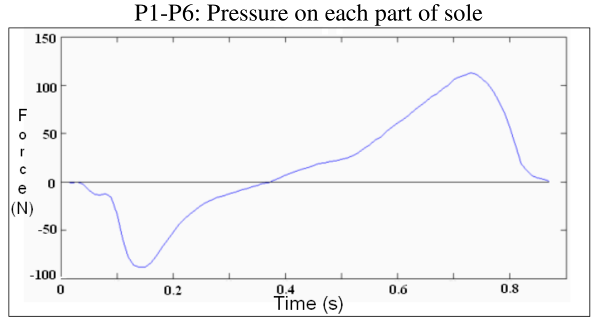

Fig. 8 Floor reaction data (direction of motion)

A part of network appears in Fig. 7. The arrows point to the number of nodes involved in a particular measurement.

As seen in Fig. 7, these data represent the relationship in the gait of a non-disabled person, and the EMG signals show that the influence of each toe on each muscle is completely different. The advantage with this model is that the data can correctly express the influence of each toe as this influence changes during gait at every 10% level node. With this model, we are able to express the different influences of the various factors when the muscular activity level is low or high. Since these features cannot be expressed by means of regression analysis, the proposed method appears to be effective for gait analysis.

V. Evaluation of the Model

We examined the three estimation models employing unused gait data to establish a means for evaluating the Bayesian network model. We determined three sets of muscular activity data as the response variables and used the other data as the predictor variables. The accuracy rates were as follows: TA 76.9%; PL 85.9%; and Ga 85.6%. We checked the accuracy rates of each activity level of the three muscles. The accuracy rates of the TA 30% level node, PL 30% level node, and Ga 10% level node were especially low. These low accuracy rates were caused by the following two factors.

First, many data were around the 30% or 10% level in both the control term and propulsive term. As an example, we present one set of EMG measured data for the TA in Fig. 9. It is clear that the data in this range fall into two types: data of the first type show considerable variation; those of the second type show a gentle curve and much less variation. From this result, it is evident that the evaluation criterion should depend heavily on the latter type of data and that many of the data of the first type offered poor estimation. The difference in the estimation accuracy is caused by the different roles of the muscular activity with the two types of data.

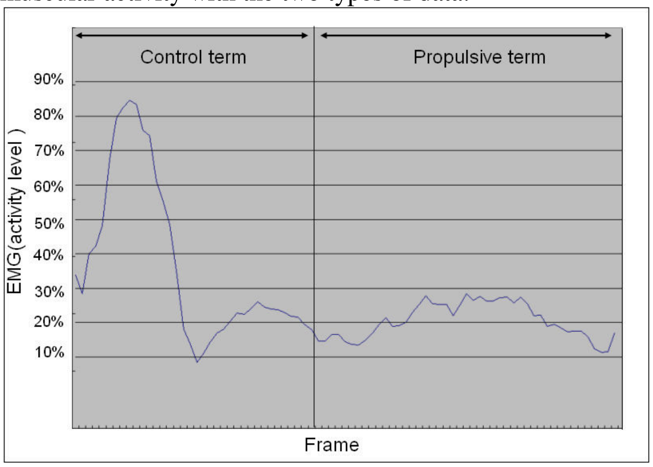

Fig. 9 Distribution of muscular activity (TA)

Second, these muscles operated in a different fashion in the control and the propulsive term. As an example, we present the parent node of the active level of TA in the stance phase in Table 1.(10%-90% mean muscle activity level or each parameters level of maximum measured value in tables.) We show the parent node of the active level of TA in the control and propulsive terms, respectively, in Tables 2 and 3. (Among all the gait measurements, there were no data at the 70% or 90% activity level in the propulsive term.) The accuracy rate of muscular activity estimation is presented in Fig 10.

From the above data, three points are evident. First, the control term and the propulsive term have a completely different parent node and conform to the situation in actual gait. For example, TA works in a low-level manner as an antagonist muscle against plantar flexion of the ankle in the propulsive term (Table 3).

Second, stance-phase data is not equal to the data which add the control term to the propulsive term: the result is a divided model that better reflects the actual features in gait.

Third, two divided models produce better results than the stance-phase model. These models are able to estimate with an accuracy rate greater than 90%

From the above results, we can conclude that Bayesian network method is effective in estimating muscular activity.

VI. Conclusion

We proposed a new method for estimating muscular activity of the foot and built an estimation model based on gait. The distinctive feature of this method is that it uses a Bayesian network.

We measured sole pressure, motion, and muscular activity of the foot during normal walking. From the data thus derived, we built an estimation model using a Bayesian network.

Table 1 Parent node of each active level (stance phase TA)

Stance Phase TA	1st	2nd	3rd
10%	Pressure on Hypothenar eminence 30%	Angle of 5th toe 90%	Pressure on Thenar eminence 20%
30%	Angle of knee 60%	Pressure on 5th toe 70%	Pressure on Thenar eminence 80%
50%	Angle of knee 60%	Pressure on Calcaneus 40%	Angle of ankle 90%
70%	Angle of knee 70%	-	-
90%	Angle of knee 70%	-	-

Table 2 Parent node of each active level (control term TA)

Control term TA	1st	2nd	3rd
10%	Pressure on Thenar eminence 80%	Pressure on Hypothenar eminence 40%	Pressure on Hypothenar eminence 20%
30%	Angle of 3rd toe 80%	Pressure on Hypothenar eminence 20%	Pressure on Calcaneus 40%
50%	Angle of knee 60%	Angle of ankle 90%	Pressure on Calcaneus 40%
70%	Angle of knee 70%	Angle of 5th toe 90%	-
90%	Angle of knee 70%	Angle of 1st toe 80%	-

Table 3 Parent node of each active level (propulsive term TA)

Propulsive term TA	1st	2nd	3rd
10%	Pressure on Hypothenar eminence 40%	Angle of 5th toe 90%	Pressure on Thenar eminence 80%
30%	Pressure on 5th toe 70%	Pressure on Thenar eminence 80%	Pressure on Outside metatarsus 80%
50%	Pressure on Calcaneus 40%	-	-
70%	-	-	-
90%	-	-	-

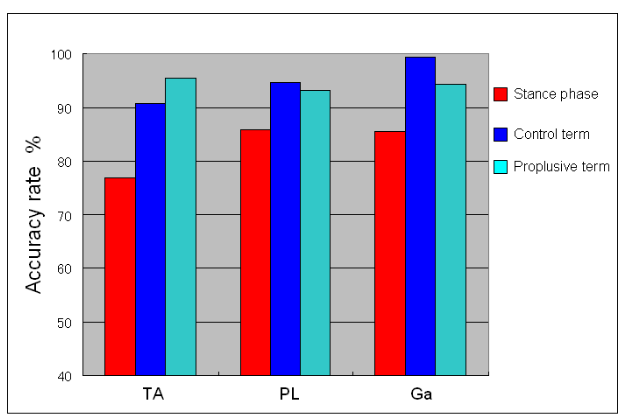

Fig.10 Accuracy rate of muscular activity estimation

This model was then divided into two models by means of the direction of the floor reaction force. The proposed new model has three advantages. First, it can express the influence of different factors that change during gait; this is because we use every 10% level node. Second, the model can express differences in the influence of the various factors based on a high or low muscular activity level. Third, the divided models reflect the features during actual gait.

In the near future, we intend to increase the number of test subjects and build an advanced model that can estimate multiple activities in a person's gait with an AFO. We will then increase the number of measurement parameters used in our model to include a knee-ankle-foot orthosis.

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