Developing an ankle-foot muscular model using Bayesian estimation for the influence of an ankle foot orthosis on muscles

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Abstract—The objective of this study is to develop an estimation model of foot-ankle muscular activity for designing an ankle-foot orthosis with a training function. We built a Bayesian network model [1] and chose three muscles to confirm its effectiveness. Such a model needs to include all factors affecting the gait, for example, speed reflex movements, joint angles and so forth. In an experiment, we examined the normal gait of a non-disabled subject. We measured the muscular activity of the lower foot muscles by electromyography, the joint angles by using statistical methods, and the sole pressure on each part of the sole. From this data, we obtained the causal relationship at every 10% level of these factors. Our model has three advantages. First, it can express the influences, which change throughout the gait, because we use 10% level nodes of each factor. Second, it can express the influences of factors, which are different for low and high muscular activity levels. Last, the model can compensate the missed estimations by estimating every 10% level muscle activity. In an evaluation of this model, we confirmed that this model can estimate all muscular activity level with an accuracy rate greater than 90%.

I. INTRODUCTION

The number of people with leg disabilities has been increasing rapidly due to the high incidence of cerebrovascular and other diseases in recent years (Fig. 1) [2]. As part of the walking assistance and rehabilitation for these disabled people, foot orthosis plays an important role in the convalescent phase and in the chronic phase. The type of foot orthosis depends on the disorder (Fig. 2). Using an ankle-foot orthosis (AFO) enables patients to resume their normal social activities at an earlier time and it is helpful for rehabilitation. However, if suitable training is not performed or the proper orthosis is not chosen, the muscular power of patients will be seriously weaken, and they will forget the start timing for moving their muscles in walking gate. Consequently, patients who do not receive appropriate rehabilitation may depend on the AFO exceedingly longer time than patients who receive appropriate rehabilitation. Obviously, this is not the optimal situation for most patients. And it causes an increase of medical expenses for public health systems. In addition, limiting the flexibility of lower limbs has a negative influence on the information input into the central nervous system. [3]

Therefore, we think that an AFO should fix only the minimum number of joints necessary, because this will help prevent the patient from relying on the AFO longer than needed.

Fig. 1 Diseases which cause lower limb paralysis

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 [4] and an orthosis with a ferrofluid brake at the ankle joint [5] (Fig. 3). These new orthoses enable more natural walking and natural use of muscles by fixing the minimum necessary number of joints or limiting the timing. However, these projects last approximately ten years and are very expensive; these two factors pose a barrier for creating new and more desirable orthoses. One solution to this problem is to estimate the effectiveness of a new AFO before development. It is helpful for prevent failure in the last stage of projects.

The objective of this study is to develop a foot-ankle muscular model for designing an AFO. The model needs to consider all factors of gait, for example, speed reflex movements, joint angles and so forth.

Some research on the 3D kinematics of a foot model has been conducted. Delp et al. created OpenSim and simulated the whole body [6]. It was developed as open source so it can be used by many researchers. Kim et al. created a 9-segment foot model for normal walking [7]. This model has three dimensions. Takashima et al. performed a dynamic model analysis of the human foot [8]. It contains arch joint and one
metacarpophalangeal (MP) joint. However, these models need actual measurements for each condition and simplify or ignore some factors. Our proposed model can evaluate muscle activity using Bayesian network estimation, a well-known statistical method. It is a graphical model of the determined theory which expresses a set of random variables and those conditional dependencies via a directed acyclic graph. [1]

This model is indispensable for making an improved foot orthosis and can almost certainly be applied to other fields of orthosis or rehabilitation.

![Fig. 2 Variety of lower leg orthoses](image1)

Some researchers use Bayesian to predict muscle activity[10]. But Bayesian estimate is not always get good results. So we build the foot muscular activity model with 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 ten 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 New lower leg orthoses](image2)

![Fig. 4 Nodes of the Bayesian Network](image3)

### II. APPROACH

We built the muscular activity estimation model using a Bayesian network to estimate the influence of the orthosis on the muscles of the lower limb. The Bayesian network builds a causation model from the joint probability of several phenomena to estimate the probability of the desired phenomenon under a certain condition. As an example in another field, Bayesian estimation can discriminate spam mail by filtering combinations of various words in emails [9].

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

a) It can build a statistical model that reflects factors which are omitted or oversimplified in the physical model.

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

c) Not only can it estimate the result from a cause, but also it can estimate a cause from a result.

![Fig. 5 Normal gait](image4)

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

The purpose of measuring muscle activity and motion of the foot during walking is to confirm the effectiveness of the muscular activity estimation method that uses the Bayesian network model. The subject was a non-disabled male in his twenties. In the experiment, the subject walked without shoes or an ankle-foot orthosis (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 joint, ankle joint, Metatarsophalangeal joint (big toe, 3rd toe, 5th toe)

**Sole pressure:** Big toe, 5th toe, Thenar eminence, Hypothenar eminence, Outside metatarsus, Calcaneus (Fig. 6)

**Other:** Floor reaction force.
We used the following devices: EMG sensor (Biometrics Co., Ltd) for measuring the muscular activity, digital goniometer (Biometrics Co., Ltd) for measuring the angles, BIGMAT (Nitta Co., Ltd) for measuring the sole pressure, and a force plate (AMTI Co., Ltd) for measuring the floor reaction force.

The MP joint is the root joint of the toes. It is rarely used to measure the gait. However, in this research we wanted to know the relevance of the toes to the EMG, because the importance of toes for gait has been reported previously in various studies [11] [12]. As shown in these studies, the toes are effective in stabilizing the body during walking.

We previously discussed the influence of the AFO on the MP joint [13]. By analyzing the sole pressure while walking with and without the AFO, it was found that the load is lightly applied to the forefoot when the AFO is worn. This implies that load is not applied to the MP joint. After several years of AFO use, this lack of load applied to the MP joint can have a negative influence on the patient’s recovery. Thus, it is necessary to measure the angle of the MP joint. We measured the sole pressure of the toe part and the angle of the MP joint.

We built an estimation model of the foot muscular activity during the gait from the data listed in the previous section. We used the data of all trials for construction of the network and 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 the gait. The data were divided into ten levels between the maximum activity level and the minimum activity level, and these levels were used as the node thresholds. We chose the K2 algorithm [14] for the search procedure. K2 algorithm is a variety of greedy algorithm and the technique of adding the node which determines parent node candidate to all the nodes and to which a score becomes high one by one as a parent node.
We show the full network in Fig. 7. The arrows point to the number of nodes involved in a certain measurement. As shown, the concentrations of the 80% level node and the 90% level node of the angle of the ankle affect many nodes. These concentrations imply that many measured factors change rapidly when the ankle extends. In other words, the network reflects the actual foot movement.

Part of the network is shown in Fig. 8 (TA at 30% level, PL at 30% level, Ga at 30% level, other nodes at 30% level and 60% level). Three groups of nodes are found in this network, beginning at the top: angle of joint nodes, pressure on each part of the sole nodes, and EMG nodes. We have to prevent circulation of the causation; therefore, an arrow cannot turn from the bottom group to the upper group.

Below is an example of three EMG nodes (bottom group). The nodes show that TA has causality to the sole pressure of the calcaneus with 30% level and 60% level. Therefore, the probability of exceeding the 30% level of muscular activity level increases. When pressure is exerted on the calcaneus, the reflected TA works to aid plantar flexion gradually when the heel is in contact with the floor.

In contrast, Ga has causality to the sole pressure of the big toe and 5th toe with 30% level. However, unlike TA, it does not have causality to the sole pressure of the big toe and 5th toe with 60% level, because when high sole pressure is on the toes of the other foot contacting the floor, the Ga does not need to support the body weight.

PL has causality to the sole pressure on the calcaneus, outside metatarsus, and hypothenar eminence. This is because the PL works against the inversion of the foot. The network therefore reflects the realities of an actual gait.

As stated above, these data show the relationship of a non-disabled person’s walk, and the EMG signals show that the influence of each toe on each muscle is completely different. The advantage is that the data can express the correct influence when the influence of the factor changes during the gait of every 10% level nodes. We express the feature that the influence factors are different when the muscular activity level is low or high. Such a feature cannot be clarified by regression analysis.

Therefore, the proposed method is useful for gait analysis.

### V. EVALUATION OF THE MODEL

We examined the model using the unused gait data to construct a model for evaluation of the model. We determined three muscular activity data as the response variables, and the other data as the predictor variables. The accuracy rates are shown in Table 1 and Table 2. From the results, PL and Ga can estimate over 80%, but the accuracy rate of TA is low. Table 2 shows each activity level of the accuracy rates of TA. As shown in this table, the 30% level node is especially low.

We show the EMG measured values of TA in Fig. 9 to examine the cause of the low accuracy of this estimation. We can see that the data in this range fall into two types. The data in the first part are higher with considerable variation. The data in the second part are gently sloping with much less variation. From this result, we can say that the criterion depends heavily on the latter data and much data in the first part miss the estimation. The missed estimation is caused by the difference role of muscular activity in the two parts.

#### Table 1 Accuracy rate of muscular activity estimation (Each test result)

<table>
<thead>
<tr>
<th>Stance phase</th>
<th>Test 1</th>
<th>Test 2</th>
<th>Test 3</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>TA</td>
<td>47.5%</td>
<td>76.9%</td>
<td>55.7%</td>
<td>60.0%</td>
</tr>
<tr>
<td>PL</td>
<td>85.9%</td>
<td>86.4%</td>
<td>74.5%</td>
<td>82.3%</td>
</tr>
<tr>
<td>Ga</td>
<td>80.9%</td>
<td>85.6%</td>
<td>85.7%</td>
<td>84.1%</td>
</tr>
</tbody>
</table>

#### Table 2 Accuracy rate of muscular activity estimation of TA (Each activity level result)

<table>
<thead>
<tr>
<th>Muscular Activity</th>
<th>10%</th>
<th>20%</th>
<th>30%</th>
<th>40%</th>
<th>50%</th>
<th>60%</th>
<th>70%</th>
<th>80%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy rate</td>
<td>85.7%</td>
<td>58.4%</td>
<td>51.9%</td>
<td>56.2%</td>
<td>87.0%</td>
<td>81.8%</td>
<td>84.4%</td>
<td>87.1%</td>
<td>89.6%</td>
</tr>
</tbody>
</table>

### VI. IMPROVEMENT OF THE MODEL

We improved the estimation model based on the outcome of the experiment and evaluation. We built two models: one is the first part of the stance phase and the other is the second part of the stance phase.

Muscular activities have different roles between the nearly heel contact and the nearly toe off, the data of the stance phase was divided into a control term (0%–20% GC (gait cycle)) and a propulsive term (20%–50% GC) (Fig. 10). Because 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.

We divided the measurement data by the floor reaction force. Fig. 11 shows the vertical direction of the floor reaction force and 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 against the floor and the body accelerates. Thus, the propulsive term is always positive.

Table 3 Accuracy rate of muscular activity estimation

<table>
<thead>
<tr>
<th>Control term</th>
<th>Test 1</th>
<th>Test 2</th>
<th>Test 3</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>TA</td>
<td>88.9%</td>
<td>91.6%</td>
<td>91.8%</td>
<td>90.7%</td>
</tr>
<tr>
<td>PL</td>
<td>96.4%</td>
<td>92.9%</td>
<td>94.9%</td>
<td>94.7%</td>
</tr>
<tr>
<td>Ga</td>
<td>98.7%</td>
<td>99.6%</td>
<td>100%</td>
<td>99.4%</td>
</tr>
</tbody>
</table>

Table 4 Accuracy rate of muscular activity estimation

<table>
<thead>
<tr>
<th>Propulsive term</th>
<th>Test 1</th>
<th>Test 2</th>
<th>Test 3</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>TA</td>
<td>95.0%</td>
<td>97.3%</td>
<td>94.2%</td>
<td>95.5%</td>
</tr>
<tr>
<td>PL</td>
<td>90.8%</td>
<td>94.5%</td>
<td>94.2%</td>
<td>93.1%</td>
</tr>
<tr>
<td>Ga</td>
<td>90.5%</td>
<td>95.7%</td>
<td>96.7%</td>
<td>94.3%</td>
</tr>
</tbody>
</table>

This time, the two models were built using the Bayesian network. The results are shown in Table 3 and Table 4. In each term, every muscle activity can estimate with an accuracy rate over 90%. In particular, the result of Ga in the control term accuracy rate is nearly 100%. It is because, as shown in Fig. 12, almost all of the data surround the 10% level of the control term so it is very easy to estimate. This method offers another significant advantage in that it compensates the missed estimation. As mentioned above, in this estimation method, we estimate every 10% level of the muscle activity node. For example, if the timing of the muscle estimation result is like that shown in Table 5, we can narrow the result down to the 40% level or the 60% level.

Table 5 Example of an estimation result

<table>
<thead>
<tr>
<th>Muscular Activity</th>
<th>10%</th>
<th>20%</th>
<th>30%</th>
<th>40%</th>
<th>50%</th>
<th>60%</th>
<th>70%</th>
<th>80%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

The probability of a missed estimation two times in a row is at most (100%-90%)^2=1%. Thus, the probability is unlikely to deviate from correct data by more than 20% (for example, 60% to 40%, or 50% to 70%).
VII. CONCLUSION

We proposed a new method for estimating the muscular activity of the foot and built an estimation model based on the gait. This method has the distinctive feature of using the Bayesian network.

We measured sole pressure, motion, and muscular activity of foot during normal walking. From the data of these measurements, we built an estimation model using Bayesian estimation. This model was divided into two models based on the direction of the floor reaction force.

This model has three advantages. First, it can express the influence of each value, which changes during the gait, because we use every 10% level node. Second, the model can express the differences of the influences of each value based on a high or a low muscular activity level. Last, it can compensate the missed estimation and narrow it down by estimating the 10% level of each muscle activity.

Therefore, the constructed model can express the muscular activity almost perfectly by this method.

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

REFERENCES

http://www8.cao.go.jp/shougai/whitepaper/index-w.html