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State Estimation of Walking Phase and Functional Electrical Stimulation by Wearable Device

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Abstract— **Functional electrical stimulation (FES) is useful to improve the gait of patients with peroneal nerve palsy or spastic hemiparesis after stroke. So as to apply FES to such patients, we have to have estimators for detecting the timing of phase switching in walking motion. We designed a wearable device for state estimating of walking and functional electrical stimulation. We consider the implementation of artificial neural network (ANN) into the device, and propose a method for supervised learning of the ANN. Two experiments have been conducted to show the effectiveness of the wearable device. The accuracy of estimating the timing for FES is good enough for the practical application.**

I. Introduction

Patients with peroneal nerve palsy or spastic hemiparesis after stroke may have troubles on their lower limbs while walking. The symptom is called as talipes equines or drop foot. Functional electrical stimulation (FES) is useful to improve the gait of such patients. The online application of FES to such patients requires the state estimation of walking phase to determine the timing of electrical stimulation. The purpose of this study is to develop a wearable device for state estimation of walking phase and functional electrical stimulation.

Recently, several types of small and lightweight sensors with low powered are available for wearable devices. We have picked up on small and low-powered sensors for angular velocity and acceleration. The sensor for acceleration is a linear accelerometer which can transduce three dimensional acceleration of orthogonal directions to electrical signals. The sensor for angular velocity is a kind of gyroscope and can measure the angular velocity around an axis which is defined to the frame of sensor. In our wearable device, we use one of the triaxial accelerometer and three of the monoaxial gyros to measure the six degree-of-freedom of a lower thigh.

A low-powered micro-processor is used in our device to estimate the state of walking from the signals of the sensors and to send the commands of electrical stimulation to an electrical circuit. We have placed all the sensors, the microprocessor and the electrical circuit with a battery in a thin package.

We define four phases in walking. Those phases are divided by the following events: toe off (TO), heel contact (HC), foot flat (FF), and heel off (HO). We can catch the timing of changing over the phases from time series of joint angles. The data of the timing is used when the supervised learning on ANN is conducted. An ANN is trained by the supervised learning for estimating the four phases from the accelerations and angular velocities of the lower thigh, which are measured by the newly designed wearable device. The supervised learning on ANN is carried out on a usual personal computer with an algorithm written in a high-level computer language. The parameters of the trained ANN are sent to the micro-processor in our wearable device. This process for obtaining the estimator of walking makes it easy for us to achieve a light computational resource and the adaptability of the wearable device. In other words, the device can adapt to the characteristics changes in individuals or in recovery process of a particular patient by this role differentiation.

II. Structure of Device and the Supervised Learning

A. Structure of device

The sensor part of our newly designed device consists of a triaxial accelerometer (Hitachi Metals, Ltd., H48C) and three monoaxial gyros (Murata Manufacturing Co., Ltd., ENC-03) . The sketch of the allocation is given in Fig.1.

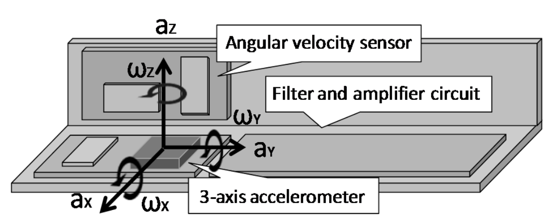

Fig.1 Allocation of sensors in wearable device.

The height, width, and depth of the sensor part with a electrical circuit of the filter and amplifier are 15[mm], 120[mm], and 15[mm]. The electric power consumption is about 3[W]. We can measure three-dimensional acceleration and three-dimensional angular velocity of a rigid body with this device. A micro-processor H8 (Renesas Technology Corp., H8) is used with these sensors for signal processing and

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controlling a circuit of electrical stimulation.

B. Supervised Learning on ANN

We take a simple feedforward type ANN for estimating walking phase. The structure is shown in Fig.2.

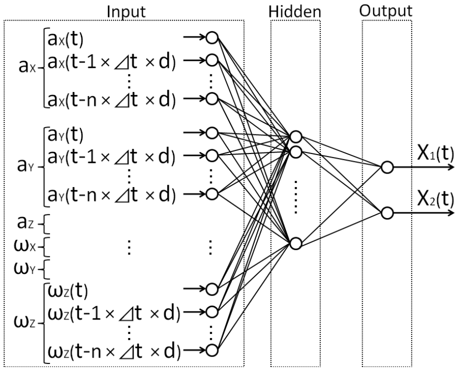


Fig.2 Feedforward ANN with delayed inputs.

The ANN is of three layer type and has not only the current sampled inputs of acceleration and angular velocity but also the past sampled ones. The input consists of three dimensional acceleration and three-dimensional angular velocity. The time traveled in the past is $\Delta t \times n$ in the case of $d=1$ and the number d indicates one instance skipping in the input sampling. Thus, the dimension of input is $6\times(n+1)$ and the maximum time traveled in the past is $\Delta t \times n \times d$. We determined the number of units in the hidden layer as eight by trial and error. The output with two units can provide two bits resolution when the ANN works as a classifier. As the states of walking, we define four phases: TH, HF, FH and HT. Those are defined as the phases between each pair of events: TO and HC, HC and FF, FF and HO, HO and TO, respectively. The output fits the classification in four walking phases. Table 1 shows the correspondence between each phase and bits of the ANN output.

Table 1 The reference values of outputs and its correspondence to walking phases.

	TH	HF	FH	HT
(X_1,X_2)	(0,0)	(0,1)	(1,0)	(1,1)
$2X_1+X_2$	0	1	2	3

We have used Levenberg-Marquardt method for the supervised learning of the ANN. The estimation by the trained ANN was not perfect. We understand that the order of the four phases in normal walking is (TH, HF, FH, HT) and how much duration of each phase occupies the proportion in walking cycle. This understanding is useful to correct the error output from the ANN. The error rate in estimating the change from HC to FF was relatively high in the experiments described below. In such cases, the computer algorithm can hold the output of FH during 0.3[sec] to reduce the error once the ANN detects a change from HC to FF.

III. Experiments

A. Experiment with Healthy Subjects

So as to detect the walking phases, we used a force plate (Kistler Japan Co., Ltd., 9286A) and a motion capture system (Motion Analysis Co., Ltd., Mac3D). We set twelve markers on the lower body of the subject for measuring joint angles. The measured angles were used to determine the walking phase. The picture of this experiment is shown in Fig.3.

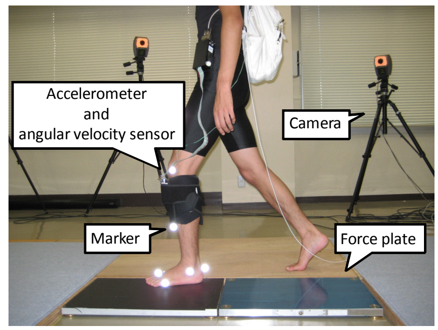


Fig.3 Picture of experiment with healthy subjects.

The designed sensor device was attached at 50[mm] below knee. We determine the position so that the electrode of FES for stimulating anterior tibial muscle can be set right below of the device and can be placed exactly on the motor point of the muscle. In most cases of drop foot patients, FES to their anterior tibial muscle can improve their gait. Exact application of FES requires determining an appropriate time duration of FES, since muscle fatigue causes another problem if FES is applied all time in walking. Therefore, the problem to estimate the timing of phase switching is the key for FES. The acceleration and angular velocity, positions of the markers, and reaction force were simultaneously recorded at sampling rate of 100[Hz]. The subjects were three healthy males of 23 years old. We asked them to walk at three different speeds. Those are normal speed, 20% slower than normal speed (slow), and 40% slower than normal speed (very slow). The strides while walking were not specified. We recorded the data of three trials in each walking speed. The data of first run was used for supervised learning of ANN, and the data of second and third runs were used for validating the trained ANN. We set d as 1 in this experiment. This means no skipping in data handling.

B. Experiment with a drop foot patient

In this experiment, the similar setup as the experiment described above was used. In addition, a hand switch was introduced for a physiotherapist to provide the timing of HO to the computer for supervised learning. The physiotherapist

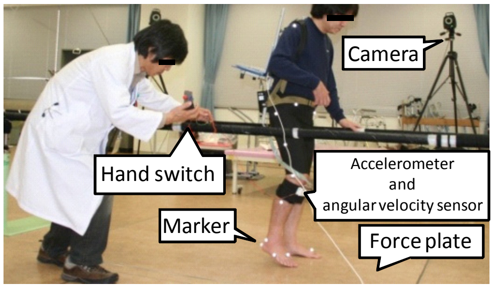


Fig.4 Picture of experiment with a drop foot patient.

walked together with the subject, and turn on the switch at HO phase based on his view of the subject's gait. The switch and physiotherapist's indication of HO make the experimental setup simple; more specifically, the force plate and the motion capture can be eliminated from the setup. This is very useful for achieving a practical setup with low cost such that the experiment of supervised learning can be carried out in common places. The subject is a patient of drop foot. We asked him walking at his usual speed. We recorded the data of six trials. Each trial included five steps. The data of first trial was used for the supervised learning of ANN, and the data of the other trials was used for validating the trained ANN. We set the skipping number d as 2 in this experiment because of the slow dynamics of his walking.

C. Definition of walking events

We define the four events of walking as follows: (1) TO starts at the instance when the floor reaction force becomes zero.. (2) HC starts when the floor reaction force takes an observable minimum value. (3) FF starts when the angle of foot-tip decreases to five degree to horizontal axis and ends the angle of foot-tip exceeds minus ten degree. (4) HO starts at the instance when the floor reaction force becomes zero.

IV. Experimental Results

A. Results of Experiment with Healthy Subjects

One of important point of state estimation is on the dimension and the selection of observed signals which can provide the exact estimation of walking phases. In other words, we like to know the minimum dimension and the best selection of observed signals for designing efficient wearable devices. We constructed two estimators of ANN. One ANN was trained with all signals of six degree-of-freedom from the sensor. The other was trained with only signals for defining movements in sagittal plane. These three signals are a_X , a_Z and ω_Y in Fig.5. The comparison of the estimation in proportion correct to all sampled time series is shown in Fig.6. There is no significant difference over all subjects between six degree-of-freedom and three degree-of-freedom.

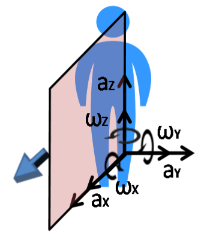


Fig5. Coordinate frame.

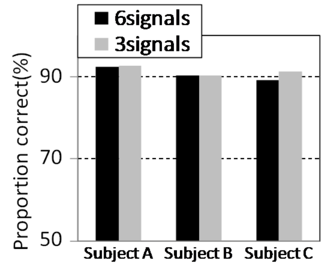
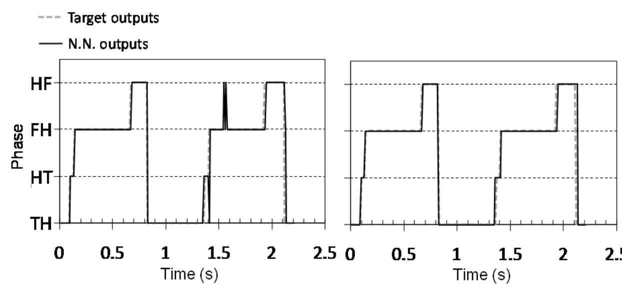


Fig.6 Comparison in accuracy.

the angle of foot-tip decreases to five degree to horizontal axis signals determining the movements in sagittal plane are enough to estimate walking phases. However, it should be noted that this experiment treated only the cases of the subjects' walking straight ahead. The signals of six degree-of-freedom will be required in the cases when subjects walk in variable manner: return, right turn, left turn, seed up, slow down, and these mixtures.



(a) Before correction. (b) After correction.

Fig.7 Example of estimation result and error correction.

The error rate in estimating the change from HC to FF was relatively high. One typical example of the error is shown in Fig.7 (a). In such cases, the computer algorithm can hold the output of FH during 0.3[sec] to reduce the error once the ANN detects a change from HC to FF.

B. Effect of input span on error rate of estimator

We do not have fully understanding of walking dynamics because the structure of musculo-skeletal system is very complex and the dynamics is described by a set of high-order differential equations. Moreover, the dynamics is not linear. This means that data set including past time responses in walking may be required to estimate walking phases. Therefore, we introduced a certain number of the time series traveled in the past as the input of ANN estimator. The effect of the numbers on the estimation error in time is shown in Fig.8. The average absolute-errors of the timings of phase switching for three subjects are given in time over three different walking speeds. The black bar in the figure indicates the case that 10 sample points traveled in the past were used as the input and the gray bar is for the case of 20 points. Since the sampling frequency was 100[Hz], the number of 10 sampled points means that the data from the current instance to the past of 0,09[sec] was used, and the number of 20 sampled points means that the data from the

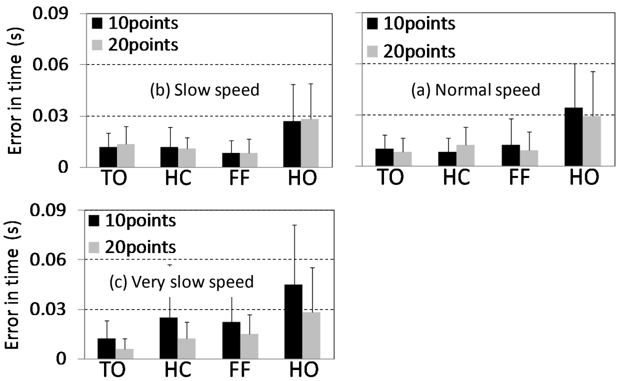


Fig.8 Average error in time of phase switching.

current instance to the past of 0,19[sec] was used. From the results, it is shown that a longer span of input is required to obtain good estimation for slow walking speed. The results also show that the estimation of timing HO is relatively difficult. An example of the output of estimator is given in Fig.9, and an example of time response of acceleration in travelling direction is given in Fig.10. From these two figures, we can understand that in last half of FF phase the variation of acceleration in travelling direction is small and this cause the difficulty of estimating the timing of switching from FF to HO. However, we achieved that the maximum absolute error of switching timings between walking phases is smaller than 0.06[sec] for all cases. This maximum absolute error is about 5% of walking cycle and is small enough for the functional electrical stimulation of drop foot patients.

C. *Results of experiment with a drop foot patient*

In the case of drop foot patient, it is difficult to detect the walking phases from the data of motion capture because the foot is always in plantar flexion. Therefore, we consider to utilize the ability of physiotherapist who can indicate the appropriate timing of HO by their experience. In this experiment, one physiotherapist walked together with the subject, and turn on the switch during HO phase based on his view of the subject's gait. The signal of this switch was recorded with another signals of wearable device and used for the reference of supervised learning of ANN. The result with sensor 's three dimensional signal in the sagittal plane is shown in Fig.11. The average of absolute error in time to estimate the timing from FF to HO was 0.035[sec] for five steps. We applied this estimator of trained ANN to the experiment of functional electrical stimulation of the same patient. The application was successful. He could walk smoothly with our wearable device without any cane.

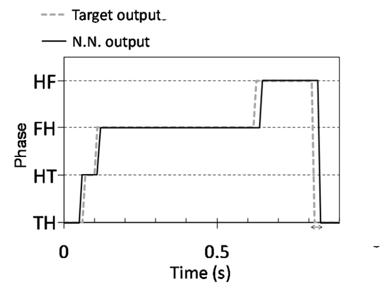


Fig.9 Example of output of the estimator.

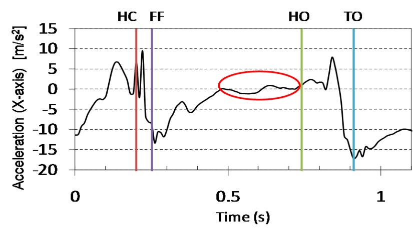


Fig.10 Example of measured acceleration in travelling direction.

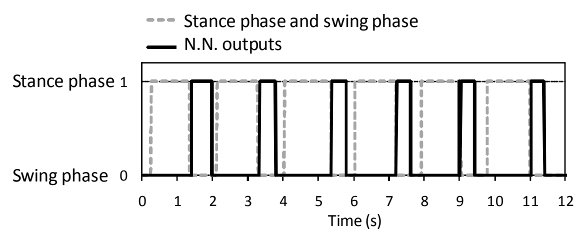


Fig.11 Example of estimation.

V. Conclusion

We have designed a new wearable device for FES which is applicable to patients with peroneal nerve palsy or spastic hemiparesis after stroke. We have implemented ANN to estimate the timing of phase switching in walking and proposed a supervised learning for the ANN. It is shown in two experiments that the accuracy of estimation is good enough for the exact application of FES to such patients. The proposed device will be useful in the practical situations to improve QOL of the patients.

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