Detecting Perturbation Occurrence during Walking

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Abstract

This research aims at the development and verification of a system that can detect the occurrence of perturbation during walking for walking-assist as soon as possible by from output signals of an artificial sensor system fitted on users' body. In this research, a back-propagation based artificial neural network (ANN) model was employed to build pattern recognition unit that can deal with the individual variation and time-varying characteristics. Results showed that the occurrence could be detected from four channels within 87.5ms, which could be considered as short enough for walking assist systems to response to the perturbation.

1 Introduction

It is very difficult for most walking-impaired people to cope with obstacles and uneven ground, and other perturbation during walking, because their afferent, efferent pathways and musculoskeletal functions were both impaired to a certain extent. As a result, the perturbation during walking becomes one of the serious risk factors for falling-down of the walking-impaired people. Thus, assist systems for the real-world environment walking, should be able to appropriately deal with the perturbation. However, most walking assist systems reported, including robotics systems [1] and those using Functional Electrical Stimulation (FES) [2] couldn't deal with the purturbation, because the research work has not taken into consideration the perturbation like uneven terrain and slip, which frequently occur in daily-life walking.

A prerequisite for building a walking assist system for daily-life is that, the perturbation could be detected after its occurrence within a period short enough for balance recovery by means of certain assistive technology, such as Functional Electrical Stimulation or robotics power assists. That is, a right triggering signal and a suitable power assist could form so called artificial reflex to help the balance recovery in the case of perturbation occurrence during walking.

Little has been done on the automatic detection of perturbation during walking. There have been research efforts to study the role of reflexes during human walking [3][4]. In [5] the role of afferent information during animal walking has been studied using a simulation model. It showed that virtual reflexes triggered by afferent informaiton could improve walking stability However, the onset of the the virtual reflexes was not sufficiently studied because the simulator "knows" the right timing to trigger the reflexes. In another research [6], a "vestibulospinal" reflex was coupled to its control mechinism of a robot dog. Since the reflex is a posture-related one, a simple threshold mechanism is enough to process gyro sensor data to trigger the reflex.

This research aims at the development and verification of a system that can detect the occurrence of perturbation during walking as soon as possible by an artificial sensor system fitted on users' body and an Artificial-Neural-Network based pattern recogintion system.

2 Method

Since responses to perturbation during walking are the results of the interaction between human neuro-musculo-skeletal system and walking environment, they might be entangled sequences of body sway and muscle activation. So that, the motion sensors that can reflect fast body motion, and sensors that can directly reflect muscle activation, should be employed. However, there has been no such measuring data available in the research field, nor research results indicating sensor combination that could result in effective detection of perturbation occurrence.

In this study, an experiment was performed to accquire the data concerning responses to the slip perturbation occurrence during walking. Then, Davis Information Criterion [7] was employed to analyze effective feature vectors for slip perturbation occurrence detection. Finally, an Artificial-Neural-Network based pattern recogintion system was built to detect the occurrence. In this study, the analyzation and detection were conducted in an off-line manner.

2.1 Measurement of perturbation occurrence during walking

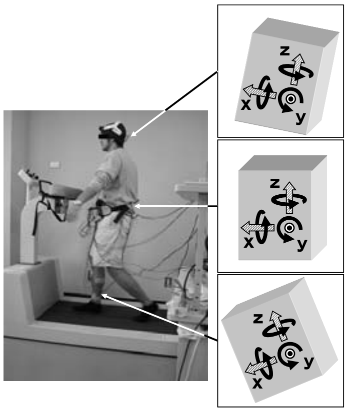

Fig.1.1. Fittings and sensitivity axial direction of each sensor

A. Subject
10 male subjects, with age 24.8±SD5.1, height 176.9±SD5.7cm, weight 68.2±SD5.9 kg and with no previous history of musculoskeletal or neurological disease, participated in the experiments. The subjects signed their written informed consent and were asked to report their dominant lower limbs prior to the experimental procedures. Besides, a pre-test (see *Procedures* for details) for safety-assurance was conducted for all subjects.

B. Equipment
8 Dry-type EMG surface differential electrodes (Model DE-2.3, DELSYS) were fitted on the skin surface above the belly of the following muscles: gluteus medius, rectus femoris , vastus lateralis, vatus medialis, semitendinosus, tibialis anterior, gastrocnemius medialis, gastrocnemius lateralis. Three 3-Axis accelerometers+gyro sensors (GYROCUBE/3A, O-navi) were fitted on the head, waist and ankle (Fig. 1.1). Two A/D cards (DAQ3024, NI) were used to collect all the sensor data, at a 1.6 kHz sampling rate. The EMG signals were amplified to 2000 times, by the pre-amp equipped in the surface EMG electrodes, and a hand-made EMG amplifier.
Perturbation to gait was realized by a split-belt (PW-21, HITACHI), for which the speed of each belt could be independently and accurately controlled from 0-3km/hr., within 270ms (200ms for PC split-belt machine communication and 70ms for speed change), which could be treated as a constant delay to control signal. The real speed was monitored using a rotary-encoder (RP-721 ONOSOKKI). A slip perturbation could be generated by slowing down one side at the moment of heel-strike.

C. Procedures
A pre-test was first applied to the subjects. In the pre-test, all subjects experienced the perturbation weaker than that would occur in the experiment, that is, the speed down from 2km/h→1km/hr, and 3km/h→1km/hr. The subjects were asked to describe their feeling, and they can decide to quit or continue the experiment. Or if the experimenters recognized that one subject is not suitable for the experiment, by observing the subject's movement and behavior, they could suggest a quit to the subject.
After all the sensors were fitted to the specified places of subjects' dominant lower limbs, each subject was asked to walk on the split-belt at a speed of 3 km/hr. The gait of the subject was monitored using x-axis accelerometer fitted to the ankle of the subject. Concretely, the heel strike was detected according to the method described in [8], which decides heel strike by comparing the peak of x-axis of accelerometer fitting to the ankle with a preset threshold (Fig. 2). After the gait reaches a steady state, that is, the heel strike to heel strike interval tends to be similar, the perturbation, a speed down (3 km/hr→0.5km/hr) would be given to the belt of the dominant side of the subject, at the moment of heel strike of the dominant lower limb. 10 perturbations would be given to a subject in one trial. Then the perturbation would be given to another side of the same subject for 10 times in another trial. That is, for each subject, 2 trials, corresponding to left and right sides, would be conducted. There was a rest for at least 10 minutes between each two trials.

2.2 Extraction and selection of feature vectors

In consideration of convenience of use in everyday life and rapidity of processing, the minimum feature vector of the artificial sensor system necessary and sufficient for the detection of perturbation occurrence should be determined. To choose the feature vectors, the Davis's cluster separation measure [7] was employed as an index to make difference between normal walking and perturbed walking. Davis's cluster separation measure could be expressed in equation (1.1)

$$f_{cc} = (u_1 + u_2)/\left|c_1 - c_2\right| \tag{1.1}$$

Where *u* and *c* are standard deviation and average of one cluster, respectively, *1* denotesof the data cluster of normal walking, and *2* denotes the data cluster of perturbed walking. The raw and Short Time Fourier Transformed (STFT) accelerometers+gyro data from head, hip and ankle were used. The Davis's cluster separation measure was calculated for each walking cycle (from heel-strike to heel-strike). The sensors and the moments with lower Davis's cluster separation measure value would be considered as the candidates for the features.

2.3 Discrimination of the perturbation occurrence from normal walking

Responses to perturbation is varing with individuals and time, therefore information processing should be able to adapt to the changes. Also because, in future, the detection of the perturbation is expected to perform in an on-line manner, an back-propagation based Artificial-Neural-Network [9], which is characterized by its learning facility, was used for pattern recognition . The inputs of the ANN include the features from the sensors fitted on foot, waist, head. The neuron number of middle layer is 10, and that of output layer is 1.Training was performed for each 40 strides using the data from all nine subjects, and test was perfomed using the data of unused 5 strides from nine subjects. If the output of the network doesn't agree with the walking condition of the test sample (that is normal or perturbed) , the data set of the subject with recoginition errors would be excluded from the training data set and added to test data set, and the training would be performed again for the remaining training data set. In addition, for the data set with at least one recognition error, another training and test would be performed for this individual subject.

3 Results

The raw data of Z-axis of accelerometers fitted on head is shown in Fig.1.2, and Davis's cluster separation measure value of the sensor is shown in Fig.1.3.

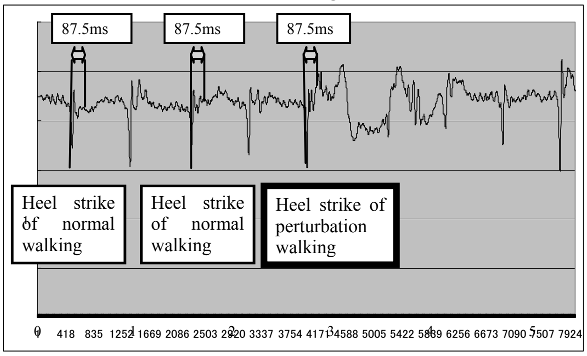

Fig.1.2. Raw data of Z-axis of accelerometers fitted on head

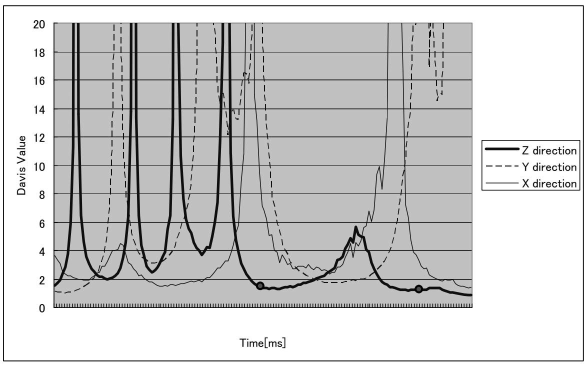

Fig.1.3. Davis's cluster separation value for Z-axis of accelerometers fitted on head

According to the these results, the feature candidates could be chosen. If the Davis's cluster separation value is lower, it might contain more information for discriminating perturbation occurrence from normal walking. The index value for all subjects is caluculated by summing and averaging the index values of all subjects. The feature candidates are listed in Table.1.1 with their index values.

Moreover, the test results when combining 3 or 4 feature candidates into sensor groups and taking the respective feature vectors as the input of of the ANN are shown in Table.1.2. The values of those feature vectors in both normal walking and perturbed walking are also shown in Fig.1.4. The horizontal axis denotes the feature candidate number, and the vertical axis shows the input value and the output value (calculation result).

Furthermore, learning curves are shown for in Fig.1.5. The vertical axis stands for the number of mis-recognition.

Table 1.1 Feature candidatesr and Davis's cluster separation value

	Feature candidates			
	sensor	**Wave pattern**	**Time(heel strike+)**	**Davis's value**
1	acceleration X-axis of ankle	original	0ms	0.893
2	angular velocity Z-axis of ankle	original	0ms	0.519
3	acceleration Z-axis of hip	original	15ms	3.92
4	angular velocity Z-axis of hip	STFT	40ms	5.27
5	angular velocity Z-axis of hip	original	40ms	6.87
6	acceleration Z-axis of head	original	50ms	2.78
7	acceleration Z-axis of head	original	87.5ms	1.47

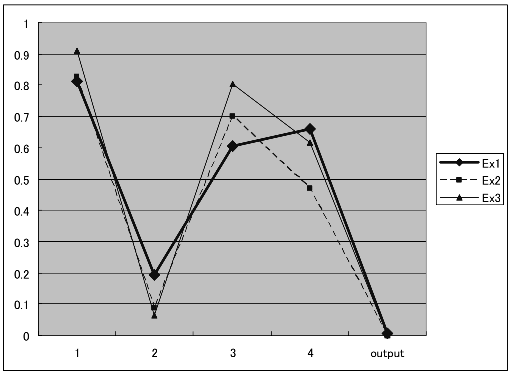

Fig.1.4.1 Feature vectors for sensor group A in the case of normal walking

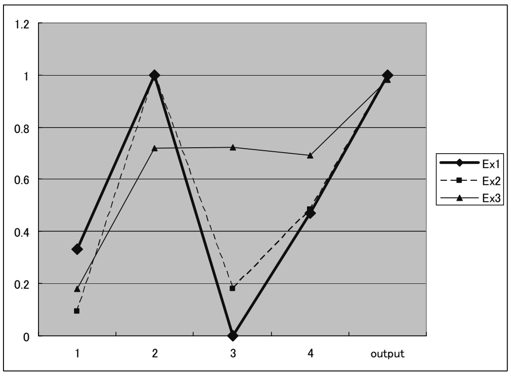

Fig.1.4.2 Feature vectors for sensor group A in the case of perturbation occurrence

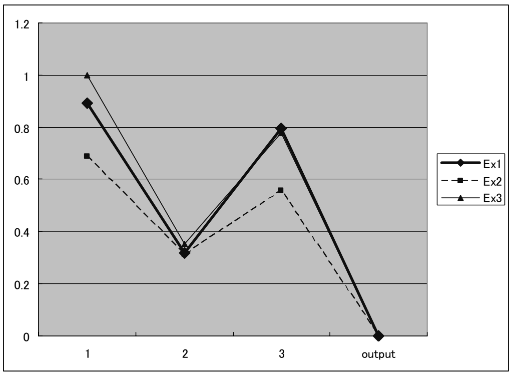

Fig.1.4.3 Feature vectors for sensor group E in the case of normal walking

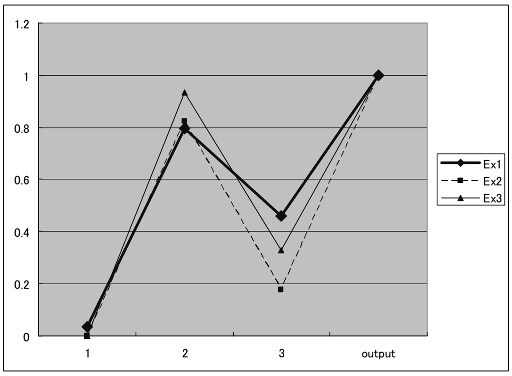

Fig.1.4.4 Feature vectors for sensor group E in the case of perturbation occurrence

Fig.1.4. Feature vectors for sensor group a and e in the case of normal walking and perturbation occurrence

Table 1.2 Judgment by ANN

Group	**feature vector**	**success rate (Training for all 9)**	**success rate (Training by oneself)**
A	1,2,4,7	45/45	-
B	1,2,7	83/85	5/5
C	1,2,5,7	82/85	5/5
D	1,2,3,6	137/141	9/10
E	1,2,6	137/141	10/10

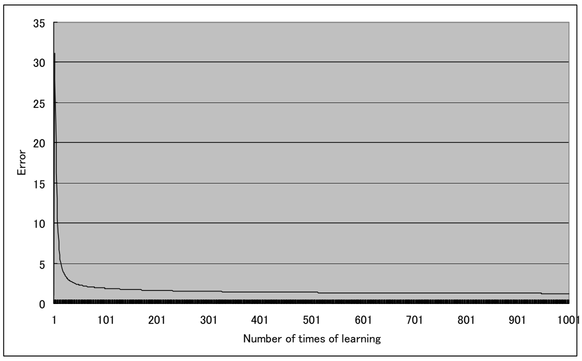

Fig.1.5.1 Learning curve for data set for all 9 subjects

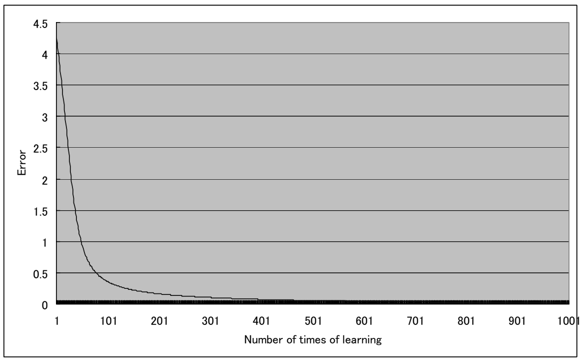

Fig.1.5.2 Learning curve for data set of one individual subject with at least one mis-recognition in the first learning trial

4 Discussion

From table 1.1 and 1.2, it is clear that feature 1 and 2 are basic features for perturbation detection. They are from X-axis acceleration of and Z-axis angular velocity of ankle Those two features could be related to the physical motion caused by the slip before the neuro-control mechanism begins to response. But these two features might be slip perturbation dependent.

The sensor groups containing feature 4,5,7 are the important

ones other than feature 1 and 2, reflecting the reflexive response of hip and head. The success rate of the test is high when these features were included in the feature vectors. However, feature 4 needs more computation for Short time fourier transform, and feature 7 needs 87.5ms after the heel-strike moment.
Sensor group e(1,2,6) could result in fast detection, however 4 samples from 2 subjects were failed.

5 Conclusion

In this study, by using ANN whose input were the selected feature vectors from an artificial sensor system containing accelerometers+gyro on hip, hip and ankle, and EMG, the possibility of detecting perturbation occurrence during walking was shown
We suppose that, the feature vectors selected by Davis's cluster separation measure are slip-perturbation dependent.
However, in order to realize an on-line perturbation detection, it is necessary to consider specialty (early detection) and generality (robust and could coped with other perturbation).

6 Acknowledgement

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7 References

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