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Speed Estimation From a Tri-axial Accelerometer Using Neural Networks

Yoonseon Song, Seungchul Shin, Seunghwan Kim, Doheon Lee, and Kwang H. Lee

Abstract—We propose a speed estimation method with human body accelerations measured on the chest by a tri-axial accelerometer. To estimate the speed we segmented the acceleration signal into strides measuring stride time, and applied two neural networks into the patterns parameterized from each stride calculating stride length. The first neural network determines whether the subject walks or runs, and the second neural network with different node interactions according to the subject's status estimates stride length. Walking or running speed is calculated with the estimated stride length divided by the measured stride time. The neural networks were trained by patterns obtained from 15 subjects and then validated by 2 untrained subjects' patterns. The result shows good agreement between actual and estimated speeds presenting the linear correlation coefficient r = 0.9874. We also applied the method to the real field and track data.

I. Introduction

Increasing concerns about health and well-being of people make regular exercise and fitness more important. Accelerometry has become a promising technique for detecting the movement of the body and estimating the energy expenditure because of some advantages such as small size, relatively low cost and measuring with minimal discomfort to the subjects [1].

There have been many studies about speed estimation using accelerometer signals. IDEEA (Intelligent Device for Energy Expenditure and Activity: MiniSun, Fresno, CA) can identify and quantify 32 types of physical activity and predict speed of walking and running [2]. Five accelerometers are attached to the body (chest, thighs, and feet) and a data collection device can be worn on the belt. This system has wires from sensors to the collection device and data are recorded on the flash memory in the device. The accuracy of speeds of walking and running was relatively high ($r = 0.986$). K. Aminian, *et al*. proposed a neural network based method to assess speed and incline from accelerometer signals from lower back (3-axis) and at the heel [3]. They trained the neural networks using treadmill data independently for each subject and applied to overground walking data. The maximum of speed-predicted error was 16%. By R. Moe-Nilssen, the study on a portable system to obtain cadence, step length, and measures of gait regularity and symmetry by trunk accelerometry was reported [4]. Kim, *et al*. designed a sensor module and a navigation computer module. The sensor module consists of a 1-axis accelerometer, a 1-axis gyroscope and a magnetic compass and it is attached on the ankle. They proposed the step, stride and heading determination methods for the pedestrian navigation system [5].

In this paper, we suggested a speed estimation method from tri-axial accelerometer signals during treadmill exercise test by subject-independent neural networks. We validated this method with untrained subjects' data and applied to the real field and track data.

II. Methods

A. System

A system which measures electro-cardiogram (ECG) and body accelerations during human exercise was designed (see Fig.1) [6]. It is composed of a chest belt with conductive

Fig. 1. Measuring system: an exercise shirt with a chest belt and a XPOD.

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Y. Song, S. Shin and S. Kim are with the Electronics and Telecommunications Research Institute, Daejeon, 305-700, Korea (corresponding author to provide e-mail: yssong@etri.re.kr).

D. Lee and K. H. Lee are with the Department of Bio and Brain Engineering, Korea Advanced Institute of Science and Technology, Daejeon, 305-701, Korea.

TABLE I.
EXPERIMENTAL PROTOCOL FOR A TREADMILL EXERCISE TEST

Stage	Time(min)	Speed(km/h)	Grade(%)
Rest	1:00	-	0
1	2:00	4.8	6
2	2:00	6.8	6
3	2:00	7.8	6
4	2:00	9.0	6
5	2:00	10.2	6
6	2:00	11.4	6
7	2:00	12.6	6
8	2:00	13.8	6
9	2:00	15.0	6
10	2:00	15.4	7.5
11	2:00	15.4	9.5
12	2:00	15.4	12.0
13	2:00	15.4	14.0
14	2:00	15.4	16.0
15	2:00	15.4	18.5
16	2:00	15.4	20.5
17	2:00	15.4	21.5
Recovery	:	1.9	-

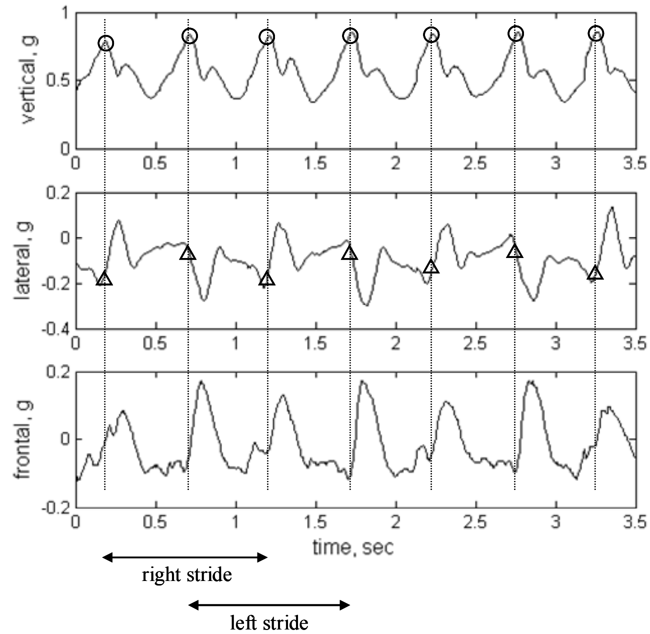

Fig. 2. Accelerometer signals during walking. circle: heel strike, triangle: determination point of left or right step.

fabric electrodes and a portable measuring device (XPOD: 68mmx36mmx13mm, 23g including a battery, CR2032). A XPOD can measure 1-channel ECG (lead I), 3-channel accelerometer signals (ADXL330, 3-axis, ±3g), and 1-channel temperature. Measured signals are digitized to 10-bits at a sampling rate of 200 Hz and can be recorded to a flash memory or transmitted to a PDA via wireless communications (Bluetooth). Signals recorded in a flash memory are uploaded to PC and analyzed. If signals are transmitted via Bluetooth, real-time analysis is possible. Conductive fabric electrodes can minimize dermal irritations because of the conductive electrode gel.

B. Experimental Procedures

17 healthy adults (all males, age 20.2±1.32 years, height 175.4±4.7cm, weight 62.7±3.74kg) walked and ran on a treadmill following the protocol of treadmill exercise test (see Table I). Subjects were requested to walk during stage 1 and 2 and they could stop their tests whenever they wanted. Signals were collected from resting stage to the each subject's stopping stage which was different by subjects (stage 10 to 12).

C. Preparation Patterns

As the speed can be calculated if the distance and the time are known, we parameterized accelerometer signals in each stride (a gait cycle, 2 steps) for assessing a stride length.

By H. Weinberg [7], walking distance was empirically determined using vertical movement. He established an approximation equation using a range of accelerometer signals measured in the vertical axis in a single stride. And K. Aminian, *et al.* [3] showed that the variances of the vertical acceleration and the time corresponding to the gait cycle are strongly correlated with speed.

As we measured the accelerometer signals on the only one position, chest, we should find a method of segmentation strides in accelerometer signals. By D. Villanueva [8], motion of the center of pressure is a result of muscle actions in the body. In the sagittal (anterior-posterior) plane, the ankle joint musculature normally acts to control the sway (ankle strategy) firstly, and in the frontal plane (medio-lateral) sway is primarily corrected by hip strategy. When the vertical accelerometer signals has a peak, it is closely correlated with a heel strike, and the lateral accelerometer signals go positive and negative alternatively by body movement from side to side as a parallelogram. It means a right step and then a left step. Fig. 2 shows a sample acceleration signals during walking. In the vertical signal, a circle means a heel strike, and in the lateral signal, a triangle means the determination point of left or right step. By this method, steps and strides can be segmented.

After each stride is segmented, we compute the ranges, the differences of the maximum and the minimum of 3 accelerations for each stride. These 3 parameters and subject's height and weight constitute an input pattern of neural networks. As subject's length of leg can affect the stride length, we introduce subject's height and weight as subject-related factors. We make a training pattern set with signals from stage 1 to stage 9. Grade information is not

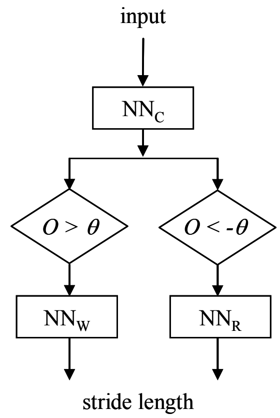

Fig. 3. Neural network structures. NN_C: walking/running classification neural network, NN_W: walking neural network, NN_R: running neural network.

considered in this study.

The target stride length is computed using a treadmill's speed and a stride time for each stride.

D. Neural Network Structures

We designed three neural networks (Fig. 3). At the stage 1, NNC, the walking/running classification network, is a two-layer perceptron with 5 input units, 10 hidden units and one output unit. It was trained by gradient descent backpropagation algorithm with momentum and adaptive learning rate. If NNC's output is over a threshold, the current input pattern is presented to the walking neural network (NNW), else if the output is below a negative threshold, the pattern is presented to the running neural network (NNR). The NNW and NNR are also two-layer perceptrons with 5 input units, 20 hidden units and one output unit. We attempted some variations only in the learning algorithms in this study, and the BFGS Quasi-Newton algorithm was selected in considering learning time, the last square root of the mean square error (RMSE) and validation performance.

III. RESULTS

The recorded three accelerometer signals are segmented to strides and the patterns corresponding to the strides with height and weight information are prepared for the neural network training. The NN_C for the classification of walking/running is trained first and then validated. NN_C's classification rate is over 99%.

The neural networks are trained first by the patterns obtained during treadmill exercise test (stage 1 ~ stage 9) by 15 subjects. Then the patterns from signals of two untrained subjects (stage 1 ~ 12) and signals of trained subjects' stage 10 ~ 12 data (15.4km/h with several grades) are presented to the networks for stride length estimation. Fig. 4 shows estimation results for the training set and the validation set. In

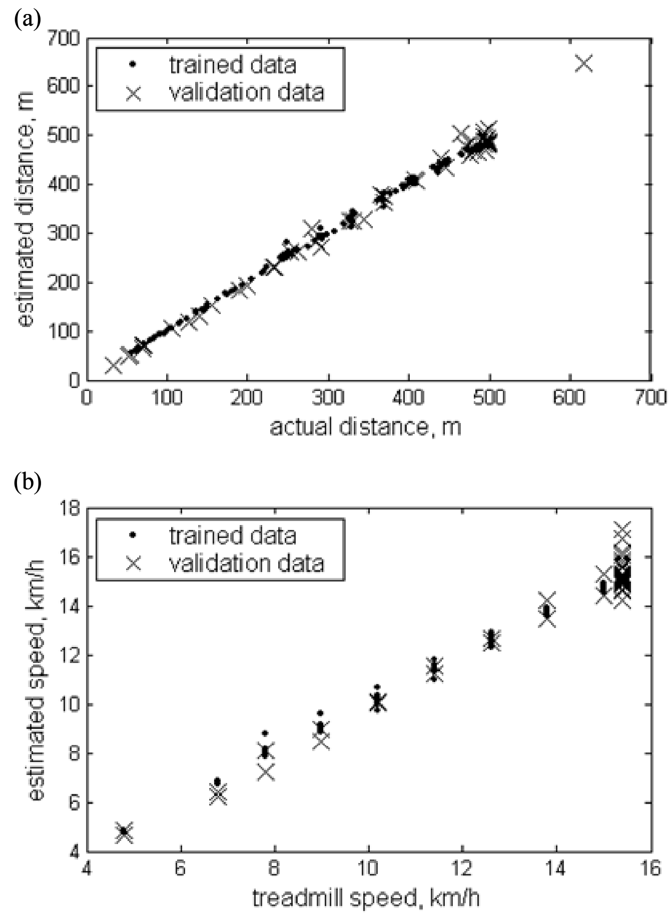

Fig. 4. Relationship between estimated and actual values of all subjects and stages. (a) distance (b) speed. dot: training data, cross: validation data.

the Fig. 4(a), there is close agreement between estimated and actual distances in each stage (r = 0.9988 for trained set, r = 0.9968 for validation set) (see Table II). Actual distances are summed of every stride lengths in each stage, and the actual stride length is computed from the treadmill speed and measured stride time. The correlation between estimated and actual speed is slightly less than distances.

In order to find a possibility of application to free running condition, this method was applied to the real track and field data. Our system measured signals from warming up to the recovery time after the end of the running. The best result can

TABLE II. COMPARISON OF THE ESTIMATED AND THE ACTUAL DISTANCES AND THE ESTIMATED AND THE TREADMILL SPEED

	data set	correlation coefficient	RMSE	range of actual value
distance	training	0.9988	6.2752m	56.37 ~ 484.71 m
	validation	0.9968	13.2190m	32.66 ~ 617.30 m
speed	training	0.9982	0.1974km/h =0.0548m/s	4.8 ~ 15.0 km/h
	validation	0.9874	0.5404km/h =0.1501m/s	4.7 ~ 17.14 km/h

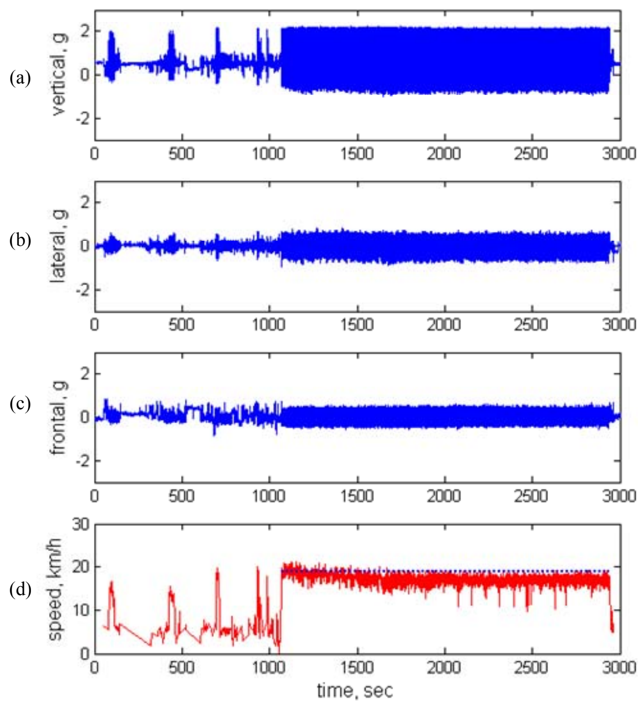

Fig. 5. Result of real track and field data, 10,000m. (a) vertical, (b) lateral, (c) frontal accelerometer signal, (d) red solid line: estimated instant speed, blue dotted line: actual average speed by record 18.97km/h, estimated average speed: 17.15km/h, relative error: 9.57%

be seen in Fig. 5, 10,000m. (a), (b) and (c) are measured tri-axial accelerometer signals and (d) is the estimated instant speed (red solid line). The game started at 1,100sec around, and the record was 31min 37.62sec. So the actual average speed can be calculated to 18.97km/h, which is plotted in a blue dotted line in Fig. 5 (d). The average estimated speed by neural network-driven stride lengths is about 17.15km/h, and the relative error is 9.57%.

IV. Discussion

The result of this study shows a good estimation of the number of steps, moving distances and speeds from acceleration signals without calibration. The speed is computed from the estimated distances and the measured time which is the same time that the actual distance is calculated with the treadmill speed.

Although this method gives good estimation in low speed, like walking, the performance is slightly poor in the higher speed. It is thought by the reason that the grade information was not considered in this study and the grade has some variations in the 15.4km/h.

In this study the network which has 20 hidden units were tried to learn. There are more possibilities in neural network training conditions like training algorithms, weight initialization methods and variable number of hidden units. In addition to acceleration signals, height and weight, other features can be considered to improve the performance. Because of this reason, the neural network structures might be modified to predict the speed instead of stride length including the time as an input parameter like R. Herren [9].

To quantify the accuracy of the method, the RMSE was calculated as well as the correlation coefficient. The average distance error is about 13.22m, when the range of actual distances is 32.66 ~ 617.30m. This error is relatively large. In the comparison of speed, the average speed error is 0.54km/h when the range of actual speed is 4.7 ~ 17.14 km/h. 0.54km/h is equal to 0.15m/s, and it means that the speed error is 15cm in one second.

Training the neural networks with a large number of patterns definitely make the method more powerful and more accurate.

V. Conclusion

A system which measures ECG and body accelerations during human exercise is designed and a speed estimation method from accelerometer signals using neural networks without calibration is proposed.

As the system can provide the number of steps, moving distances, the instant speed in every step and average speed, and the method uses the signals measured on the only one position, chest, it must be a useful system for the exercise of runners and fitness program of normal subjects with more convenience.

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