EVALUATING RECOVERY PROCESS OF NEUROLOGICAL DISORDER USING ANKLE-WORN ACCELEROMETERS

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Abstract - In this study, a gait analysis system for monitoring a patient's recovery process is proposed. The proposed gait analysis system consists of two ankle-worn accelerometers for obtaining gait signals and an android application for providing the analyzed results. To evaluate the proposed system, experiments were conducted on 20 subjects using our developed devices that are attached on the subject's both ankles. The obtained data are preprocessed with low-pass filter and moving average filter for eliminating noises. Then, the vertical components and energy values were measured to analyze gait signals. From the level of correlation between the energy values of each foot, the recovery progress is estimated. In general, correlation value of an unhealthy subject is lower than that of a healthy subject. The experimental results were shown with the correlation values. The proposed gait analyzing system can provide the recovery progress of patients after surgery.

Index Terms - Accelerometer, gait, neurological disorder, recovery process.

I. INTRODUCTION

Analyzing the gait has been used to evaluate health status. Also, the gait is an important indicator to examine body condition, it provides a diverse health information including body balance and ordinary life habit. Patients who suffered from neurologic diseases such as stroke, parkinsonism, cervical myelopathy, or lumbar spinal stenosis may need to take a surgical operation. The gait analysis can be used to evaluate a patient's recovery process after surgery. The gait analysis systems based on inertial measurement units have been developed to monitor human gait features [1-4]. The gait features such as number of strides, walking time, stride time, stride length, stride frequency, stride velocity, stride cadence, stance time and ankle range values have been analyzed through the gait systems [5, 6]. These gait systems have been validated the effectiveness to use as an evaluation indicator of therapeutic efficacy during rehabilitation. In this study, we developed a gait analysis system to evaluate patient's recovery process using two ankle-worn accelerometers.

II. METHODS

A. Equipment and Participants

As shown in Fig. 1, we implemented the gait analysis system composed of gait sensors (EBIMU-9DOFV2) [7] and an android application which acquires gait signals and displays experimental results. The developed embedded board consists of a tri-accelerometer and a Bluetooth module to analyze the gait data. Fig. 1. Prototype of the gait analysis system (a) Ankle-worn accelerometer, (b) An android application



(a) (b)

Fig. 1. Prototype of the gait analysis system (a) Ankle-worn accelerometer, (b) An android application

In this study, 20 subjects were participated in this experiments. They are 10 healthy subjects and 10 patients who are 5 patients had spinal stenosis, 2 patients had Parkinsonism, and 3 patients had cord infarction. The patients had been diagnosed by a medical specialist at the Soonchunhyang University Hospital in Bucheon, Korea. All subjects were asked to attach the gait sensors on both ankles and to complete 10 meters walk test as shown in Fig. 2.



Fig. 2. The 10 meters walk test

B. Gait Analysis Algorithm

The purpose of the pre-processing is to eliminate the high-frequency noises and reduce the participant unconscious trembles. High-frequency noise is eliminated by digital low-pass filter embedded in gait sensors. After the low-pass filtering, a moving average filter(mv-filter) was used to reduce jittering noise. The mv-filter smoothes the data by replacing each data with the average of the neighboring data. The mv-filter reduces the jittering noise such as unconscious trembles and smooths out the data. Three parameters (3, 5, and 10 points) were used respectively to find the optimal window size of the mv-filter. The 5-point filtering was set to the optimal parameter of mv-filter by observing results.

Unlike the healthy subjects, the patients who suffered from the gait disturbance showed a habit of pulling one foot. This habit which came from various reasons including a pain, stiffness, or neurological diseases prevented the patient from lifting their foot on the ground. So, we assumed that the vertical component of the acceleration signal was distinguished between patients and healthy subjects. As shown in Fig. 3, the vertical component was extracted from the accelerometer signal [8]. We converted the vertical component to frequency bands using Fast Fourier Transform(FFT) [9,10]. Also, the energy feature E was calculated by

$$E = \frac{\sum_{i=1}^{w} |x_i^2|}{w}, \quad (1)$$

where $x_1, x_2, x_3, \ldots x_i$ are the FFT components and w is the window length. The sum of FFT components is divided by w for normalization.

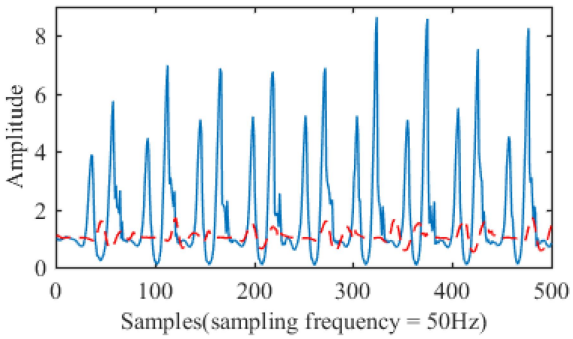


Fig. 3. Vertical component (solid: healthy subject, dashed: patient)

Correlation coefficient ρ is a method to analyze the linear relationship between two variables. ρ is calculated between each pair of axes as the ratio of the covariance and the product of the standard deviations. In this study, ρ was used to monitor a linear relationship between both feet.

III. RESULTS

In the experiments, signal energies for each foot were calculated. For calculating the signal energy, four window sizes (25, 50, 75, and 100) were tested. The bigger window size is applied, the higher signal energy is obtained. At the same time, the characteristics of gait was faded. From the result of the experiment shown in Fig. 4, the optimal window size was set to 50.

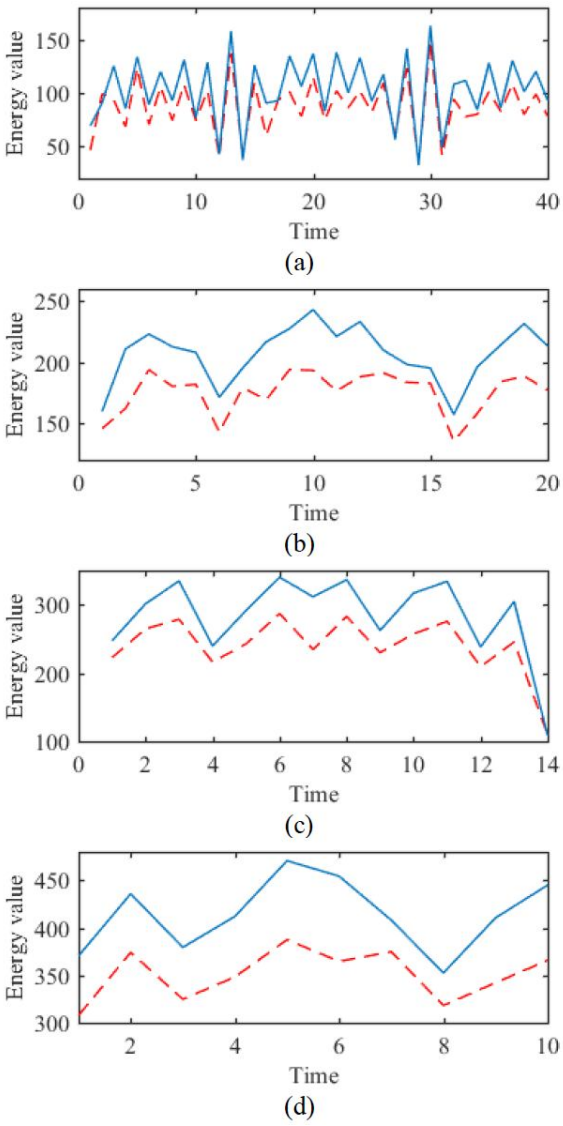


Fig. 4. (a), (b), (c), and (d) is energy value of a healthy subject with window size 25, 50, 75, 100, respectively (dashed line: right foot, solid line: left foot)

Table 1 shows two experimental results. One is that the average of signal energy obtained from the healthy subjects is more than doubles of the signal energy obtained from the patients. The other is that the averages of signal energies obtained from the patients' pre-surgery records and post-surgery records were similar. Table 2 shows the Pearson correlation value between the signal energies of each foot. As shown in Table 2, there is a strong positive correlation between left and right foot of healthy subjects. Whereas, there is a weak positive correlation between left and right foot of patients. The correlation of patients has a trend

of growing after a surgery.

Table. 1. Mean of energy value for window size 50(HS: Healthy subjects, PB: Patients before surgery, PA: Patients after surgery, L: Left foot, R: Right foot)

Subject	Mean ± Std
HS_L	252.07 ± 36.64
HS_R	252.23 ± 48.41
PB_L	118.31 ± 35.06
PB_R	101.33 ± 11.32
PA_L	107.86 ± 17.35
PA_R	103.84 ± 13.24

Table. 2. Mean of correlation value (HS: Healthy subjects, PB: Patients before surgery, PA: Patients after surgery)

Subject	Mean ± Std
HS	0.9283 ± 0.022
PB	0.5861 ± 0.064
PA	0.6899 ± 0.077

CONCLUSIONS

In this paper, we have presented a gait analysis system composed of a gait sensor and a smartphone application. the vertical components of each foot were extracted. Then the signal energy of each vertical component was calculated. The correlation between the signal energies of each foot is calculated. The signal energies of healthy subjects are bigger than those of patients. The correlation between left and right foot is positive for all the subjects. The correlation of healthy subjects is bigger than that of patients. The correlation value is different depending on health status after the surgery on the patients. In the future, we will conduct experiments on more subjects to evaluate our proposed system.

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