AN ANKLE SPRAIN RECOGNITION SYSTEM FOR IDENTIFYING ANKLE SPRAIN MOTION FROM OTHER NORMAL MOTION USING MOTION SENSOR

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The purpose of this study was to develop an ankle sprain recognition system which identifies ankle sprain motions from other normal motions. Six healthy male subjects performed a total of 600 simulated ankle sprain motions and normal sports motions. Eight motion sensors were attached to cover the whole foot segment to monitor the linear velocity and angular accelerations of the segment. The data obtained from the motion sensor at the medial calcaneus selected to train up the Support Vector Machine (SVM). The trained SVM model was then verified by another 600 trials from other six healthy male subjects. Among the 300 sprain trials, 291 (97.0%) of them were identified correctly. However, there was still a 14.3% false alarm which normal trials being identified as sprain trails. In general, a good accuracy of 91.3% was achieved.

KEY WORDS: accelerometer, gyrometer, signal identification.

INTRODUCTION: Ankle sprain is one of the most common ankle injuries in sports (Fong et al., 2007), accounting about 12% of total sport-related cases admitted to the accident and emergency department (Fong et al., 2008). In order to protect the ankle from sprain injury, our research team is developing an intelligent sprain-free shoe. The idea of the sprain-free shoes is to protect from ankle sprain injury while allowing freedom of motion during normal activities. The sprain-free shoes consist of a recognition system which identifies ankle sprain motion to activate the protection mechanism while the ankle is at risk of sprain injury. In this paper, the ankle sprain recognition system using motion sensor and Support Vector Machine (SVM) is introduced.

Fig 1: A subject performing simulated sprain motion on a mechanical ankle sprain simulator

METHODS: Data Collection: Six male subjects (age = 21.2 ± 1.7 yr, height = 1.72 ± 0.05m, body mass = 61.5 ± 3.1kg, foot length = 255.3 ± 10.6mm) with healthy ankles were recruited. The university ethics committee approved the study. Each subjects contributed to 100 trials, including 50 trials of simulated ankle sprain motion and 50 trails of non-sprain normal motions. The simulated sprain motions were conducted on a mechanical ankle sprain simulator (Fig 1, Chan et al., 2008). Different combination of inversion and plantarflexion (total inversion, 23 degrees supination, 45 degrees supination, 67 degrees supination and total plantarflexion) were performed. The sprain simulator performed 30 degrees angular perturbation along the rotation axis when the shutter released. Non-sprain motion included walking, running, jump-landing, cutting and stepping-down were performed in a random sequence in a motion laboratory. Ten trials from each motion were done.

Eight wired motion sensors (Sengital Ltd., Hong Kong, China) were attached as shown in Figure 2. These attachment positions allowed a full coverage of right foot and ankle segment. Each motion sensors consisted of a tri-axial gyrometer which measured angular velocities (G_x, G_y, G_z), and a tri-axial accelerometer that measured linear accelerations (A_x, A_y, A_z). Therefore a total of 48 signals from all sensors were collected at a frequency of 500Hz.

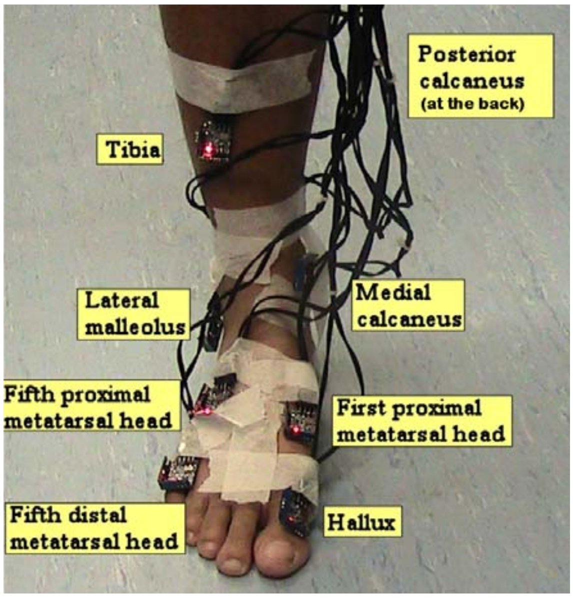

Fig 2: The attachment of the 8 motion sensors

Data Analysis: The data collected were used to train up the Support Vector Machine for the development of the identification system. The learning theory of SVM can be expressed as a function:

$$f : \Re^n \rightarrow \pm 1$$

Where *y = f(x)*. This function maps patterns *x* to the classification *y*. the function *f(x)* can be expressed as:

$$f(x) = \sum_{i=1}^{N} y_i \alpha_i k(x, x_i) + b \qquad - (1)$$

where *N* is the number of training patterns, (x_i, y_i) is training pattern *i* with its classification as y_i , α_i and b are learned weights, and *k* is a kernel function (Cristianini & Shawe-Taylor, 2000):

$$K(\bar{x}_i, \bar{x}) = \Phi(\bar{x}_i) \cdot \Phi(\bar{x}_j)$$

k can be any symmetric kernel function that satisfy the Mercer's condition corresponds to a dot product in some feature space (Bernhard et al., 1998). (x_i, y_i) with $\alpha_i > 0$ are denoted as support vectors. The surface where $f(x) = 0$ is a hyperplane through the feature space as defined by the kernel function. Optimal parameters α_i and b are selected to minimized the number of incorrect classifications by maximizing the distance of the support vectors to the hyperplane $f(x) = 0$. $y_i > 0$ indicate a simulated supination sprain trail, where $y_i < 0$ indicate a non-sprain trial.

Maximize:

$$L_D \equiv \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} y_i y_j \alpha_i \alpha_j k(x_i, x_j) \quad \text{-(2)}$$

subject to:

$$0 \le \alpha_i \le C, \quad \sum_{i=1}^{N} y_i \alpha_i = 0 \qquad \text{-(3)}$$

The constant C denotes the penalty to errors, therefore it affects the tolerance to incorrect classifications. After solving the equation (2) and find α_i, we can use any other support vector (x_i, y_i) to find b.

A value of signal strength (unitless) was calculated for each of the eight sensors to quantify its ability to identify the spraining and non-spraining motions. SVM training was then done with the data from the motion sensor with highest signal strength. One second (500 frames) of data from all the six channels of that sensor were processed by Discrete Fourier Transform (DFT) and was converted to frequency domain. The converted data was then used to train up the SVM (Joachims, 1999).

Model Validation: Another six subjects (age = 22.0 ± 1.7 yr, height = 1.75 ± 0.04 m, body mass = 69.7 ± 2.8 kg, foot length = 262.0 ± 9.9 mm) took part in the validation test and contributed to a total of 600 trials. The same protocol was done for data collection as in the previous part. The accuracy of the recognization system was calculated by the percentrage of trials being correctly identified. The SVM training was considered successful when the accuracy reached 90%. If the SVM training was not successful, the training process would be performed again with the sensor with the second highest signal strength and so on. If SVM training with a single sensor was not successful, combinations of two or more sensors will be performed.

RESULTS: The sensor located at medial calcaneus was found to possess the highest signal strength among all the sensor location. Therefore, data from the sensor located at medial calcaneus were chosen to train up the SVM. After training the SVM with 600 simulated sprain and non-sprain trials, 521 support vectors and the threshold b = 0.46397071 were selected to built up the SVM model in equation (1).

The SVM model was then went through the validation test. 600 trails simulated sprain and non-sprain trials from another six subjects were feed into the SVM model. 548 out of 600 trials were identified correctly. Therefore the accuracy was 91.3%. Details of results of validation test were shown in table 1. The SVM model built was considered successful, and further training using other data was abandon.

Table 1 Results of validation test

	Correctly identified trials	**Incorrectly identified trials**	**Total**
Simulated sprain trials	291 (97.0%)	9 (3.0%)	300 (100%)
Non-sprain trials	257 (85.7%)	43 (14.3%)	300 (100%)
Total	548 (91.3%)	52 (8.7%)	600 (100%)

DISCUSSION:

There was 91.3% accuracy for the trained SVM model which was considered to be very good for biomechanics studies. For the 300 simulated sprain cases, 291 trials (97.0%) were identified correctly. As this device is going to act as the activation signal of the intelligent sprain-free shoes, the alarm can be activated at 97% of the cases while the ankle is at risk of sprain motion. However, for the 300 non-sprain cases, there were 43 trials incorrectly identified trials, which made the false alarm rate be 14.3%. This indicates a gap and needs for improvement.

In order to improve the accuracy, data from two or more sensors can be adopted to train up the SVM model. The trade off of using more than one sensor is the increased amount of data to be processed. Hence, the process time and system requirement will be increased.

Therefore we have to make a balance between accuracy and process time. On the other hand, the SVM model developed was for young male subjects. In order to fit the model to individual of different homogenous groups, the whole procedure can be repeated. Therefore, we can come up with different SVM models which suits different homogenous groups.

The current recognition system only allows data processing after data collection, but not real time recognition. Data trimming and discrete fourier transform were need to be done after data collection. In order to achieve real time identification, further investigation has to be done on immediate analysis. Application of sliding window would be possible approach. The SVM model real time data analysis can be built on a printed circuit board. The wireless prototype can be made at a cost of around US$100. In order to lower the production cost for mass production in the future, further investigation have to be done, for example, reducing the sampling rate of the sensor and sliding window, which can lower the cost of the sensor, as well as the processing unit of the recognition module.

All the simulated sprain motion was performed on a mechanical sprain simulator. The sprain simulator can only perform sub-injury motions instead of real sprain cases due to ethical reasons. No ligamentous injury was introduced. Therefore we could only rely on the simulated sprain motion which is less vigorous to train up the SVM model.

CONCLUSION: This study developed an ankle sprain recognition system which identifies ankle sprain motions from other normal motions. The system consists of one motion sensor of 500 Hz sampling frequency and a recognition model. An accuracy of 91.3% was achieved. The system can be further developed for the real time identification of ankle sprain injury in the intelligent ankle sprain free shoes.

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