Towards a Human Airbag System Using μIMU with SVM Training for Falling-Motion Recognition

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***Abstract*-A Micro Inertial Measurement Unit (μIMU) which is based on MEMS accelerometers and gyro sensors is developed for real-time recognition of human body motions, specifically falling-down motions caused by slippage. A μIMU measures three-dimensional angular rates and accelerations. With an integrated microcontroller, the overall size of our μIMU is less than 26mm*20mm*20mm. We present our progress on using this μIMU based on Support Vector Machines (SVM) training to recognize falling-motions. The digital sample rate of the micro controller is 200 Hz which ensures rapid reaction to short falling time and also gives a sufficient database for SVM recognition. Experimental results show that our system can achieve a lateral falling-motion recognition rate of 100% using selected eigenvector sets generated from 200 experimental sets. Our goal is to implement this system to a human airbag system designed to protect hip fractures of the elderly.**

Keywords: MEMS, μIMU, Human Airbag, Human Motion Sensing, SVM

I INTRODUCTION

Falls and fall-induced fractures are very common among the elderly. Of all the fall-induced fractures, hip fractures account for most of the deaths and costs. After a hip fracture, an elderly person usually loses his/her independence of functional mobility, and hence, has poor quality of life. The elderly is also more susceptible to experience a second hip fracture [1]. Hip protectors are protective devices made of hard plastic or soft foam and are placed over the greater trochanter of each hip to absorb or shunt away the energy during mechanical impact on the greater trochanter [2]. They are widely demonstrated both biomechanically and clinically to be capable of reducing the incidence of hip fractures. However, the compliance of the elderly to wear them is very low, due to discomfort, wearing difficulties, problem with urinary incontinence and illness, physical difficulties, and not useful and irrelevant. Our group is proposing to develop a novel hip protector with smaller dimensions and greater comfort according to the body figures of the elderly. Basically, a MEMS motion sensing unit will be used to detect imbalance of the elderly and trigger the inflation of compact air bags worn by the elderly. The system design is small, light-weight and comfortable as the elderly have to wear it everyday.

Owning to the availability of low-cost, small-size MEMS sensors, it is possible to build self-contained inertial sensors with overall system dimension of less than 1 cubic inch, and at the same time, the sensors unit can track the orientation and locomotion in real time. As an example, our group developed the Micro Input Devices System (MIDS) based on MEMS sensors as a novel multi-functional interface input system, which could potentially replace the mouse, the pen and the keyboard as input devices to the computer [3]. The MIDS was also used to evaluate the performance of PD adaptive control and impedance control schemes in manipulating a five-fingered robot hand and in manipulating this hand to grasp a ball [4, 5]. A similar but more complex device was also developed by X.P. Yun et al. to track rigid body orientation in real time [7] and to serve as a navigation system for small autonomous underwater vehicles.

Our group recently developed a micro Inertial Measurement Unit (μIMU) which measures three-dimensional angular rates and accelerations. This system is similar to the one developed by X.P. Yun et al. but has a different hardware configuration and uses different software protocols. Our system is optimized for overall system volume and cost. With an integrated microcontroller, the overall size of the μIMU can be designed to be less than 26mm*20mm*20mm. The μIMU is an essential part of the novel hip protector, which can collect human motion data and also recognize motion data, e.g., falling-motion, if trained appropriately using Support Vector Machines (SVM) algorithm. Experiments showed that the recognition rate of the falling-down motion of subjects can be as high as 90%. Hence, this intelligent μIMU unit can be eventually implemented onto our novel hip protector design for activation of airbags.

This paper is organized as follows. In Section 2, a brief idea of our hip protector design will be introduced. We will focus on describing the μIMU design in Section 3, including hardware and software. The SVM training process will be discussed in Section 4. Experiments and data analysis will be described in Section 5, before the conclusion is presented in Section 6.

II HIP PROTECTOR SYSTEM

As mentioned before, hip fractures account for most of the deaths and costs of falls and fall-induced fractures, especially for elderly people. We propose to develop intelligent and personalized wearable airbags to reduce the force of impact during a fall for elderly. Recent advances in manufacturing technologies have made it possible to safely compress air in small, light weight, and low-cost pressurized cylinders, thereby making a personalized airbag system not only possible but economically feasible. In addition, a MEMS based inertia measurement unit is suitable for small, light weight hip protector system, and can be intelligently programmed to measure and recognize human motions to trigger the inflation of the airbag(s) before a subject falls to the ground.

Fig. 1 illustrates the basic concept of an intelligent hip protector system. A micro 3-D motion-sensor based belt is mounted on the waist and is worn by a subject. The motion sensing system will be fully calibrated to compensate for temperature and environmental vibration effects. Two air bags, each with about 4.5” inch inflated diameter are connected by polypropylene tubes to a small compressed air cylinder of volume less than 10 *mL*, and are embedded in the belt and are positioned on the greater trochanter of each hip. Based on our calculations, these airbags are expected to reduce the impact force during a fall by around 2000*N*.

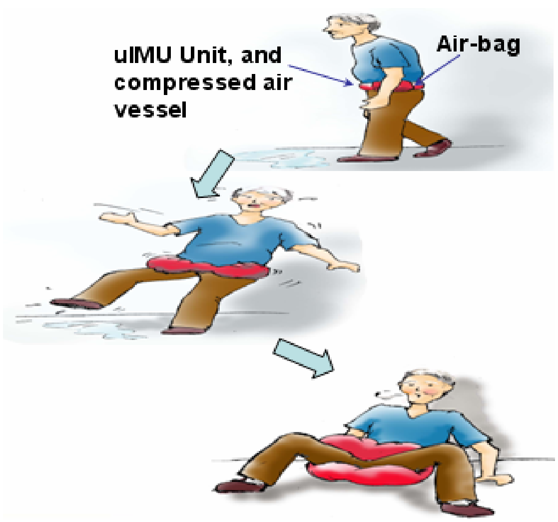


Figure 1. Conceptual illustration of the “Smart Hip Protection” system in action.

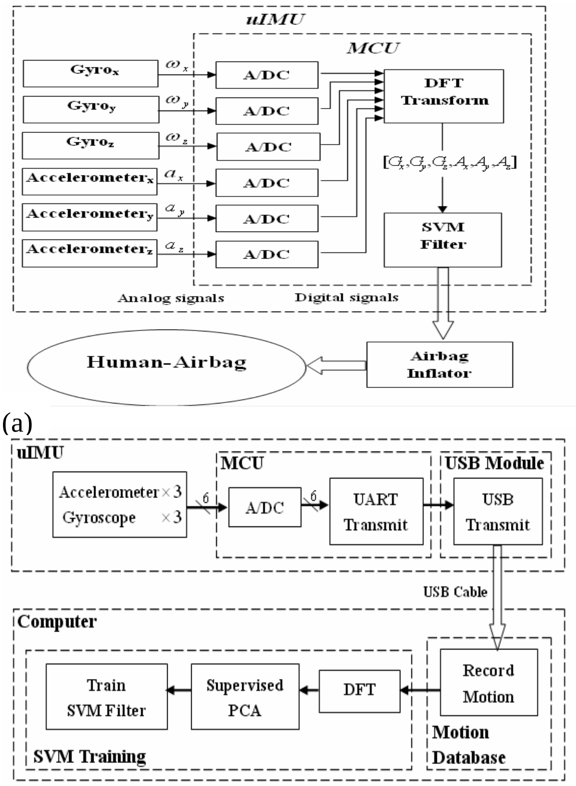
When an elderly loses balance, the MEMS micro sensors in the belt will detect his/her disorientation and triggers the inflation of the airbag on the side in a few milli-seconds before falling to the ground. The hip-airbags can be designed just like automobile airbags, which contain many micron-size holes for automatic deflation. Therefore, distension can be controlled to last for a few seconds, and the hip-airbags will gradually collapse afterwards. The force attenuation property of the inflated hip protector will be tested using the established method in our laboratory. The motion-based condition of activating the inflation process will be defined such that it is sensitive enough to detect imbalance of an elderly but not too hypersensitive to induce false alarm. To test a falling-down condition and generate a trigger signal by the μIMU is the key issue discussed in this paper.

III μIMU DESIGN

MEMS sensors play a major role in the μIMU due to their low-cost and miniaturized size. We use MEMS sensors to measure the 3D accelerations and 3D angular rates, with the coordinate transformations and filtering calculations performed by a Micro Control Unit (MCU).

A. System Description

As shown in Fig. 2, the sensor analog signals are first converted into digital signals, before the DFT (Discrete Fourier Test) transform was performed on the signals. Then, the DFT-filtered signals are compared with the SVM data to match the physical data being recorded by the sensors, i.e. if the data matches the SVM data of a falling-motion, then a “1” is generated



(b) Figure 2. Schematic chart of the μIMU. (a) Final system architecture. (b) Prototype system architecture.

to trigger the airbags. The entire μIMU includes mainly two parts: the MEMS sensors and the MCU. We used three gyroscope sensors (single-axis) and two accelerometers (dual-axes) to detect human motion. The raw sensor signal is expressed by analogue voltages of -2.5v to +2.5v each. The MCU first converts the signals to digital signals, then transmits the packed data signal sequentially via a USB chip and wire to a computer. After hundreds of experiments, which include lateral falling-down, walking, running, sitting and stepping stairs, we formed a database for Support Vector Machines (SVM) training. After training, we selected the best features as SVM filter for falling motion recognition. Then the filter program was loaded into the MCU to perform such a function in real time.

B. *Hardware*

An illustration of components of μIMU is shown below in Fig. 3. Three single-axis MEMS gyroscope sensors (ADXRS150 Analog Devices Inc.) are mounted as shown, each can test one angular rate in one direction; thus we can measure yaw, roll and pitch of the body motion. Also, two dual-axis MEMS accelerometers (ADXL311 Analog Devices Inc.) are mounted in the backside of the same PCB boards housing the gyros. The two sensors can detect the acceleration motion of an object in three dimensions.

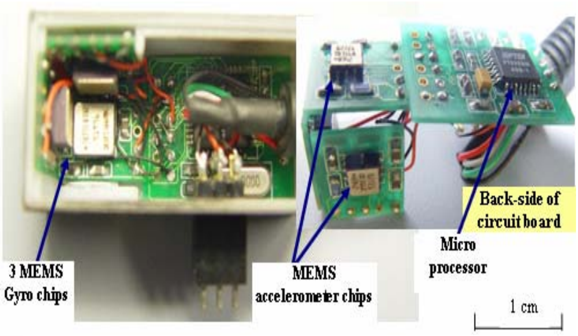


Figure 3. Photograph of a 3-D motion system consisting of 3 gyros and 3 acceleration sensors and a micro processor.

The original analog signal generated by the sensors is transmitted directly to the ADC channels of the MCU (AT Mega 8535L) After A/D transform, the digital signal is passed to the USB chip through the TXD port for transmission to PC for off-line analysis. Wireless transmission to the PC will be implemented at a later stage.

The MCU supports In-System-Programming to update software. After experiments and Support Vector Machines (SVM) training with the database, we can download new programs for motion recording and falling-down recognition. A micro battery cell will also be added to serve as power supply in the final system.

C. *Software*

The software for μIMU mainly includes 3 parts. The first part is C programming for MCU, which transforms the original analogue into digital signal and transmit data package to computer via USB module. We describe our digital signal as follows. For each angular rate and acceleration, the minimum value is 0 and the maximum value is 255, that is, 128 is the zero point of angular rates and accelerations. Then the actual value can be obtained by $F(x) = (x-128) \times K$, where for acceleration, K is equal to *1.63*m/s, for angular rate, $K=1.172$ degree/s (calculated from manufacturer's datasheets).

The second part is the data recording and analysis. As Fig. 4 shows, the computer receives all accelerations and angular rates and display in six diagrams in time domain, each represents one axis acceleration or rotation rate. At the same time, a txt file is generated consisting of six characters for DFT filtering and analysis.

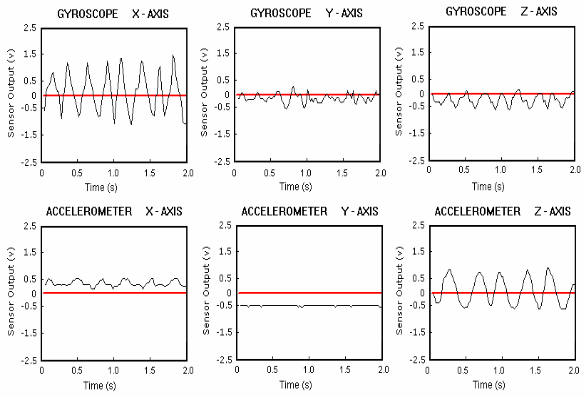


Figure 4. Time domain accelerations and rotation rates in 3 axes.

The third part is the program integrated with the SVM training features, which on one hand, will still transform analogue signals into digital data, and on the other hand, the features act as a filter. It will judge the information transformed from the sensors, i.e., if the motion is a falling state. If it is a dangerous state, the MCU will send out a signal of 1, indicates that the body is falling down, then the system will trigger the airbags for inflation.

Ⅳ SVM TRAINING FOR FALLING-DOWN RECOGNITION

Our goal is to recognize falling-motion in real-time in order to control the hip-protecting airbags. We address this classification problem as a binary pattern recognition using Support Vector Machines (SVM):

(1) Set up motion database of 'falling-down' and 'non-falling-down' by experiments wearing the uIMU;

(2) Use Supervised PCA (Principle Component Analysis) to generate and select characteristic features;

(3) SVM training and finally get the SVM filter.

A. *Supervised PCA for Feature Selection*

Feature generation and selection are very important in falling-motion recognition, as badly selected features such as weightlessness, leaning backward, and hip spinning may cause confusion with jumping, sitting and turning around, which can obviously diminish the performance of the system. Furthermore, even though the present features contain enough information about the output class, they may not predict the output correctly because the dimension of feature space may be so large that it requires numerous instances to determine the result.

Principle Component Analysis (PCA) can generate mutually uncorrelated features while packing most of the information in several eigenvectors. It is widely investigated in pattern recognition and in a number of signal and image processing applications. So in our system, we use Supervised PCA (SPCA) algorithms for feature generation and selection.

A set of eigenvectors can be computed from the training motion data and some of eigenvectors are selected for classification according to the corresponding eigenvalue. We consider that every feature encodes different information in a certain scale such as moving backward, weightlessness, moving down, etc.

We selected the eigenvectors according to the binary classified capability, instead of the corresponding eigenvalues. It is because the eigenvectors with large eigenvalues may carry the common features, but not the distinguishing information between the two classes.

The method can be described in brief as follows. Suppose that we have two sets of training samples: *A* and *B*. The number of training samples in each set is *N*. Φ_i represents each eigenvector produced by PCA. Each of the training samples, including positive samples and negative samples, can be projected into an axis extended by the corresponding eigenvector. By analyzing the distribution of the projected *2N* points, we can roughly select the eigenvectors which have more motion information. The following is a detailed description of the process.

(1) For a certain eigenvector Φ_i, compute its mapping result according to the two sets of training samples. The result can be described as $\lambda_{i,j}$, ($1 \le i \le M$, $1 \le j \le 2N$);

(2) Train a classifier f_i using a simple method such as Perception or Neural Network which can separate $\lambda_{i,j}$ into two groups: falling-down and non-falling-down with a minimum error $E(f_i)$;

(3) If, $E(f_i)<\theta$, then we delete this eigenvector from the original set of eigenvectors.

Note that, M is the number of eigenvectors and $2N$ is the total number of training samples. θ is the defined threshold. The remaining few eigenvectors after elimination by process (3) above are then selected. The eigenvectors can also be represented back to motion data representing a typical movement.

The key point is shown in Fig. 5 for evaluation of eigenvectors. The performance of Eigenvector *i* is better than that of Eigenvectors 1 and 2.

It is possible that too few good eigenvectors are selected, even none in a single PCA analysis process. We propose the following approach to solve this

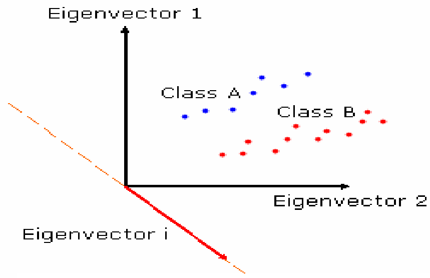


Figure 5. Different distinguishing ability of different eigenvector.

problem. We assume that the number of training samples, *2N* is large enough. We randomly select training samples from the two sets. The number of selected training samples in each set is less than *N/2*. Then, we perform the SPCA analysis with them. By repeating the previous process, we can collect a number of good features. This approach is inspired by the boot-strap method. The main idea of this approach is that it may emphasize some good features by reassembling data and then make the features stand out easily.

B SVM Classifiers

The Support Vector Machines is a new technique in the field of statistical learning theory [9]. Originally, SVM was developed from classification problems. It was then, extended to regression estimation problems, i.e., to problems related to finding the function: $y = f(\bar{x}), y \in R, \bar{x} \in R^N$ given by its measurements y_i with noise at some (usually random) vector $\bar{x}_i, (y_1, \bar{x}_1), \ldots, (y_l, \bar{x}_l)$.

In SVM, the basic idea is to map the data X into a high-dimensional feature space *f* via a nonlinear mapping Φ, and to do linear regression in this space [10]. $f(\bar{x}) = (\omega \cdot \Phi(\bar{x})) + b$

$$\Phi : R^N \to F, \omega \in F \qquad (1)$$

where b is a threshold. Thus, linear regression in a high dimensional (feature) space corresponds to non-linear regression in the low dimensional input space R^N. Note that the dot product in Equation (1) between ω and $\Phi(\bar{x})$ would have to be computed in this high dimensional space (which is usually intractable), if we are not able to use the kernel that eventually leaves us with dot products that can be implicitly expressed in the low dimensional input space R^N. Since Φ is fixed, we determine ω from the data by minimizing the sum of the empirical risk $R_{emp}[f]$ and a complexity term $\|\omega\|^2$, which enforces flatness in feature space

$$R_{reg}[f] = R_{emp}[f] + \lambda\|\omega\|^2 = \sum_{i=1}^{l} C(f(\bar{x}_i) - y_i) + \lambda\|\omega\|^2 \qquad (2)$$

where l denotes the sample size $(\bar{x}_1, \ldots, \bar{x}_l)$, C(.) is a loss function and λ is a regularization constant. For a large set of loss function, Equation (2) can be minimized by solving a quadratic programming problem, which is uniquely solvable [11]. It can be shown that the vector ω can be written in terms of the data points

$$\omega = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) \Phi(\bar{x}_i) \tag{3}$$

with α_i, α_i* being the solution of the aforementioned quadratic programming problem [10]. α_i and α_i* have an intuitive interpretation as forces pushing and pulling the estimate $f(\bar{x}_i)$ towards the measurements y_i [12]. Taking Equation (3) and Equation (1) into account, we are able to rewrite the whole problem in terms of dot products in the low dimensional input space

$$\begin{aligned} f(\bar{x}) &= \sum_{i=1}^{l} (\alpha_i - \alpha_i^*)(\Phi(\bar{x}_i) \cdot \Phi(\bar{x})) + b \\ &= \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(\bar{x}_i, \bar{x}) + b \end{aligned} \tag{4}$$

where α_i, α_i*are Lagrangian multipliers, and $\bar{x}_i$ are support vectors.

In Equation (4), we introduce a kernel function $K(\bar{x}_i, \bar{x}) = \Phi(\bar{x}_i) \cdot \Phi(\bar{x})$. As explained in [13], any symmetric kernel function K satisfying Mercer's condition corresponds to a dot product in some feature space.

For a detailed reference on the theory and computation of SVM, readers can refer to [12].

There are many kernels that satisfy the Mercer's condition as described in [12]. In this paper, we take a simple polynomial kernel in Equation (4):

$$K(\bar{x}_i, \bar{x}) = ((\bar{x}_i \cdot \bar{x}) + 1)^d \tag{5}$$

where d is user defined (taken from [10]).

After the off-line training process, we obtain the values for Lagrangian multipliers and support vectors of SVM. Let $\bar{x} = [x_1, x_2, \ldots, x_N]^T$ (x_i is an element of $\bar{x}$ and is a sample data $\bar{x}_i$ of $\bar{x}$). By expanding Equation (4) according to Equation (5), we know that $f(\bar{x})$ is a nonhomogeneous form of degree d in $\bar{x} \in R^N$

$$f(\bar{x}) = \sum_{0 \le i_1 + i_2 + \ldots + i_N \le d} c_j x_1^{i_1} x_2^{i_2} \ldots x_N^{i_N} \tag{6}$$

where i_1, i_2, ..., i_N are nonnegative integers, and $c_j \in R$ are weighting coefficients. j can be 1, 2, ..., M, where $M = \binom{N+d}{N}$.

V EXPERIMENTS AND ANALYSIS

Experiments were performed to demonstrate the motion detection in 3D space of our µIMU. We first performed experiments of lateral falling-down and other motions to form the database. After SVM training, we extracted the best features for recognition of a falling-down state, the recognition rate of the sample data can be good as 100%.

A. Motion detection experiments and database forming

Tow groups of experiments were done. One hundred times of lateral falling-down and one hundred times of other motions, including 10 times running, 20 times walking, 20 times sitting, 20 times squat, 20 times stepping stairs and 10 times jumping. The reason for selecting these motions is that they are the normal motions of life. For the elderly, they seldom jump and run, hence we collected more sitting and squatting motion data, in addition to the fact that these motions are more similar to the motion during a fall. Time-sequenced pictures of an experimental subject during a fall are shown in Fig. 6.

Figure 6. Lateral falling-down motion.

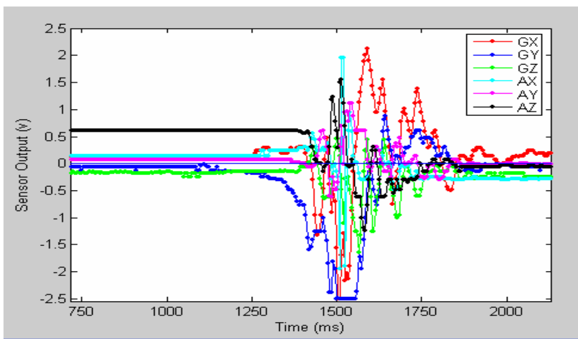


Figure 7. Original motion data recording of falling-down.

Fig. 7 shows the original data of motion including 3D accelerations and rotation rates from one experimental trial. *GY* in Fig. 7 (blue color) is the angular rate of the pitch direction, hence we can judge a falling motion starting from the changing of *GY*. *AZ* (black color) is the acceleration in the vertical direction. A sudden spike in this data corresponds to when the hip hits the ground. By synchronizing visual observations with the sensed data, we extracted the motion data from beginning of a fall to when the body hits the ground (soft mat) for all 6 sensors. Examples of the motion data from the 6 sensors through this short duration(~350ms) of motion is shown in Fig. 8. Fig. 9 is the Discrete Fourier Transform (DFT) result, which records information in frequency domain. One hundred falling-down experiments were done including different falling-motions and the experiments were also performed by two different people for construction of a more realistic database. These experimental data are used for falling-down reference.

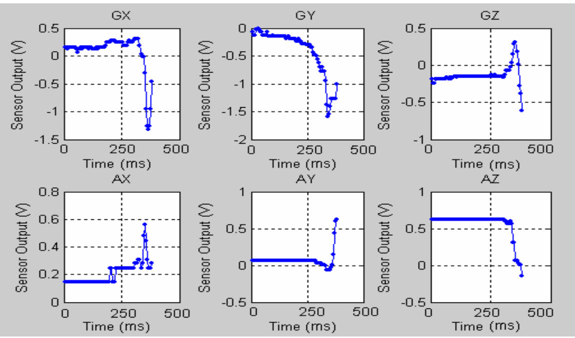


Figure 8. Sensor data extracted from the motion of a subject from beginning of fall to impact.

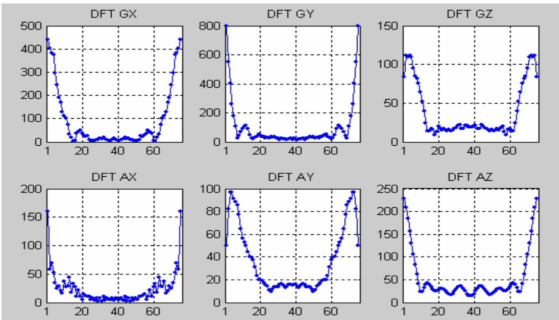


Figure 9. DFT transform result v.s. frequency of falling.

Fig. 10, 11 and 12 show the corresponding motion data from the sensors when a subject is running. In Fig. 11 and 12, only one cycle of data is extracted for analysis.

B. SVM training and falling-down recognition

As mentioned earlier, we recorded 200 experimental results, 100 of which were from motions of 'falling-down', and the other half of 'non-falling-down'. Each result consisted of 6 arrays measured data by the 6 sensors respectively. Every result has different array length because the motion periods are different.

We performed data pre-processing to filter noise and reduce dimension. For each experiment result, we performed DFT with the 6 arrays of data. We kept the

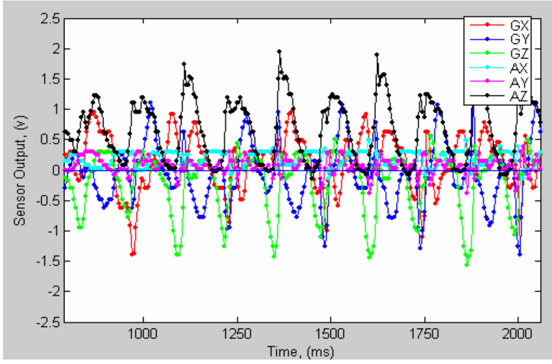


Figure 10. Original motion data from forward running motion.

first 10 order of each DFT result. Then, we obtained a matrix of 200 rows and 60 columns, each row represents one experimental set, with 6*10 sequence of DFT processed *Gx, Gy, Gz, Ax, Ay, Az* data.

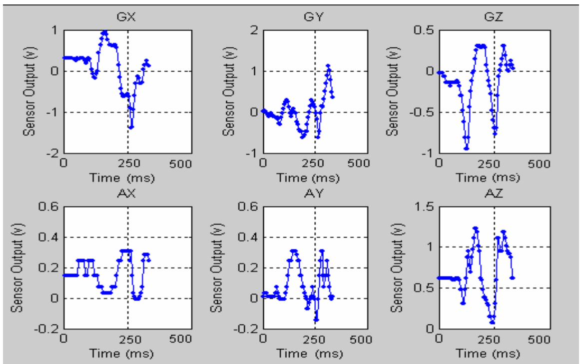


Figure 11. Data from one cycle of running motion.

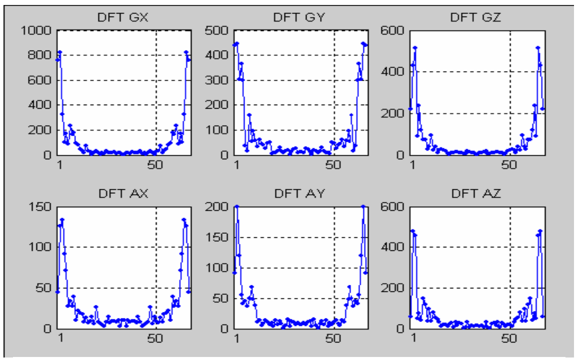


Figure 12. DFT transform result V.S. frequency of running

Then we selected the good vectors as training features. After 213 SPCA, we obtained 175 good eigenvectors. But the feature information by one eigenvector may not be sufficient enough. Thus we randomly selected out three eigenvectors from the 175 eigenvectors and performed the SPCA. After 3152 times of selection, we obtained 87 good triple sets. After testaments, we found our measuring and training system can be used to classify the experimental results excellently. All the top

9 eigenvector sets can classify the 200 vectors into 'falling-down' and 'non-falling-down' with 100% confidence.

Table 1. The coefficient of SVM classifier

c_0	-2.084349241	c_5	0.00000498
c_1	0.007279936	c_6	-0.000000173
c_2	-0.003962637	c_7	0.000000374
c_3	-0.002182333	c_8	-0.000001469
c_4	-0.000003207	c_9	0.000002342

Hence, we can randomly choose a triple set for SVM training and obtain the coefficients of SVM filter (as shown in table 1), i.e., the coefficients can be used in equation (6) to find $f(\bar{x}_i)$:

$$f(x_1,x_2,x_3)=c_0+c_1\cdot x_1+c_2\cdot x_2+c_3\cdot x_3+c_4\cdot x_1^2 +c_5\cdot x_1\cdot x_2+c_6\cdot x_1\cdot x_3+c_7\cdot x_2^2+c_8\cdot x_2\cdot x_3+c_9\cdot x_3^2 \quad (7)$$

We will use this SVM classifier to categorize future experimental data collected for random human motions and determine a percentage of confidence for the µIMU system. Also, since the filter is in the form of algorithm operation, the calculation time is very short, and thus can be implemented in the MCU for real-time data processing.

VI Conclusion

This paper presents a novel MEMS based Micro Initial Measurement Unit (µIMU) for detection of complex human motions and recognition of falling-down motion. The µIMU will eventually be used as the sensing and trigger part of a human airbag for a hip-protector system. The µIMU can now measure human motion data of acceleration and rotation rate in 3 dimensions. With an integrated microcontroller, the small size unit can transmit experimental data to a computer for real time or post-experiment data analysis. We also used SVM as a pattern recognition method for training after PCA for the DFT data. We have shown that selected eigenvector sets can classify 200 experimental data sets that were used to generate the eigenvectors into 'non-falling-down' or 'falling-down' with 100% confidence. We are currently collecting more random human motion data to test the selected eigenvector sets. We expect the correctness of falling-down recognition will be close to 100% using the SVM training technique developed by our group.

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