Development of a Human Airbag System for Fall Protection Using MEMS Motion Sensing Technology

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***Abstract*-This paper describes the development of a human airbag system which is designed to reduce the impact force from falls. A Micro Inertial Measurement Unit (µIMU), based on MEMS accelerometers and gyro sensors is developed as the motion sensing part of the system. A recognition algorithm is used for real-time fall determination. With the algorithm, a microcontroller integrated with the µIMU can discriminate falling-down motion from normal human motions and trigger an airbag system when a fall occurs. Our airbag system is designed to have fast response with moderate input pressure, i.e., the experimental response time is less than 0.3 second under 0.4MPa. In addition, we present our progress on using Support Vector Machine (SVM) training together with the µIMU to better distinguish falling and normal motions. Experimental results show that selected eigenvector sets generated from 200 experimental data sets can be accurately separated into falling and other motions.**

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

I INTRODUCTION

It is well known that the world is facing an increasely aging population. With this increase, the proportion of frail and dependent elderly is also likely to increase significantly [1]. This shift in demographic pattern will lead to an exponential increase in the number of elder individuals suffering from injury of falls, i.e., falls and fall-induced fractures are very common among the elderly.

Hip fractures account for most of the deaths and costs of all the fall-induced fractures. Apart from causing physical injury, hip fracture can result in significant psychological trauma and lead to self-imposed restrictions of activity that can compromise the quality of life of the individual [2]. 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 [3]. 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, problems with urinary incontinence and illness, physical difficulties, and them being not useful and irrelevant. Our group is developing a novel hip protector with smaller dimensions and greater comfort for the elderly. Basically, a MEMS motion sensing unit will be used to detect imbalance and trigger the inflation of compact airbags worn by the elderly.

Two key issues have to be considered for the human airbag system. One is a comfortable compressed airbag that can be inflated instantly. Another is a small triggering device embedded with a rapid and accurate algorithm for recognizing falling motion. For the fast inflated airbag, we first utilize an electromagnetism valve as a switch to open a compressed air source. When the valve is triggered, an airbag can be inflated in less than 0.3 second under 0.4Mpa, which is enough to effectively reduce the impact force on the hip due to a fall. Now, an independent airbag is under development based on compressed CO2 cartridges. In this paper, we will focus our discussion on the triggering device and the motion-recognition algorithm.

Due 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 sensing unit can track the orientation and other motions 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, pen and keyboard as input devices to the computer [4, 5]. We also developed a micro Inertial Measurement Unit (µIMU) which measures three dimensional angular rates and accelerations based on MEMS sensors. This system is similar to the MIDS but has a different hardware configuration and uses different software protocols. A USB port was designed for data transmission on the µIMU. With the µIMU, we recorded human motion including normal motions and falling. An algorithm SVM (support vector machine) was used to analyze the data recorded by the small MEMS unit [6].

Recently, we integrated a microcontroller and Bluetooth module on the µIMU, and the overall size of the unit is 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 wirelessly and also recognize motion data, e.g., falling-motion using recognition algorithm. A mechanism of triggering the airbag is also developed and we proved that triggering an airbag system by the µIMU is feasible.

Generally, most complicated pattern recognition problems involve the identification of dynamic and time-varying signals, such as speech recognition, handwriting recognition, and image sequences identification. Signals of MEMS sensor output concerning daily physical activities are of low frequency, transient and dynamic in nature. In [1], an eigenvector based pattern recognition method was utilized to initiate multidimensional signal identification to analyze MEMS accelerometers data. However, the sensing unit did not use gyro sensors, and consequently, a lot of rotation information was not utilized. A better classification result for recognition of different human motions was reported by Himberg et al. [7], who utilized independent component analysis and principal component analysis and they achieved 83-90% accuracy. We present our progress on using our μIMU with Support Vector Machine (SVM) training to recognize falling-motions in this paper. Experimental results show that selected eigenvector sets generated from 200 experimental data can be separated into falling and other motions successfully.

This paper is organized as follows. In Section 2, a brief idea of a human airbag system to reduce impact force on hips will be introduced. Section 3 will focus on describing the systematic design including the μIMU and a compressed air inflation system. In Section 4, real time recognition of falling-down motion will be discussed. The algorithm of SVM training process will be discussed in Section 5, before the conclusion is presented in Section 6.

II HUMAN AIRBAG SYSTEM FOR FALLING PROTECTION

As mentioned before, hip fractures account for most of the 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 the 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 tractable, but economically feasible. In addition, a MEMS based inertia measurement unit is suitable for a 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.

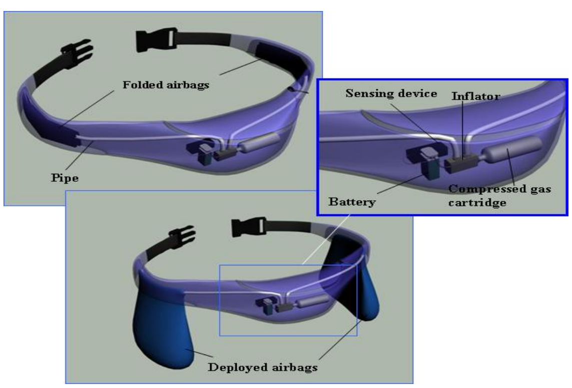

Fig. 1 Conceptual illustration of the “intelligent” human airbag system in action.

Fig. 1 illustrates the basic concept of an intelligent human airbag system. Initially, the airbag is compressed in a belt. When an elderly loses balance, the MEMS micro sensors in the belt will detect his/her disorientation and triggers the inflation of the air bag 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 hypersensitive and induce false alarms. Testing for a falling-down condition and generating a trigger signal via the μIMU is the key issue discussed in this paper.

Ⅲ SYSTEMATIC 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. Coordinate transformations and filtering calculations are performed by a Micro Control Unit (MCU). The MCU also controls the triggering of the inflation of the airbags. The airbag inflation system is designed as a rapid response mechanism which can inflate the airbags very quickly when an electronic signal indicating falling motion is generated by the motion sensing part.

A. *μIMU design*

We use the ATMEL ATmega32 microcontroller in the design. The microcontroller has 32Kbyte flash, 2Kbyte of SRAM, 8 channels of 10-bit ADC, and an USART (Universal Synchronous and Asynchronous serial Receiver and Transmitter) port [8]. The Bluetooth module is connected with the microcontroller by the UART at a baud rate of 56.2 KHz.

For our experiments, we use ADXL203 and ADXRS300 sensors as accelerometers [9] and angular rate gyros [10], respectively. These sensors are produced by Analog Devices, and are low cost and relatively high performance sensors with analog signal output. The output signals of the accelerometers (a_x, a_y, a_z) and the rate gyros (ω_x, ω_y, ω_z) are measured directly with an A/D converter inside the microcontroller. The digital sample rate of the microcontroller is 200 Hz, which ensures rapid reaction to human motion. Three gyroscope sensors (single-axis) and two accelerometers (dual-axes) were used in our system.

The accelerometers and the gyros act as a micro inertial measurement unit (μIMU) of the motion sensing system. These μIMU sensors and the Blue tooth module are housed on a small PCB, as shown in Fig. 2. Two Li battery of 3.6V can power the unit for 3 hours.

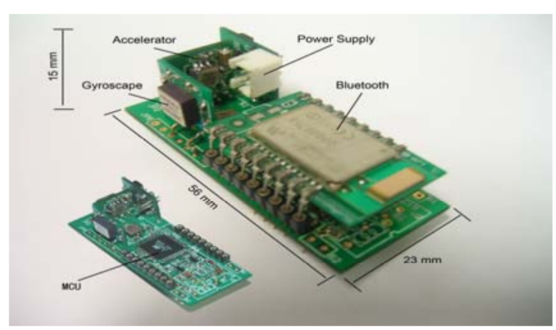

Fig. 2 Photograph of a 3-D motion sensing system consisting of 3 gyros and 3 acceleration sensors.

We adopt a TDK Systems blu2i Module in our system to transfer data to a host system [9]. This Bluetooth module provides easy integration to various host systems. The module is directly connected to the microcontroller via a USART port. The module is very small in size (69mm*24mm*5mm) and can easily communicate with the microcontroller.

Thus, the µIMU can realize two functions: 1) data collection and transmission to the computer wirelessly, which can be analyzed or trained using a SVM; 2) a recognition algorithm can be downloaded to discriminate a falling motion, and trigger the airbag for inflation.

B. Experimental airbag system setup

As mentioned before, it is possible to safely compress air in small, light weight, and low-cost pressurized cylinders. Therefore, to the problem of opening a cylinder and releasing the gas to the airbag rapidly is a key issue for the airbag system. We designed an experiment to test with what pressure the inflation system will work the fastest.

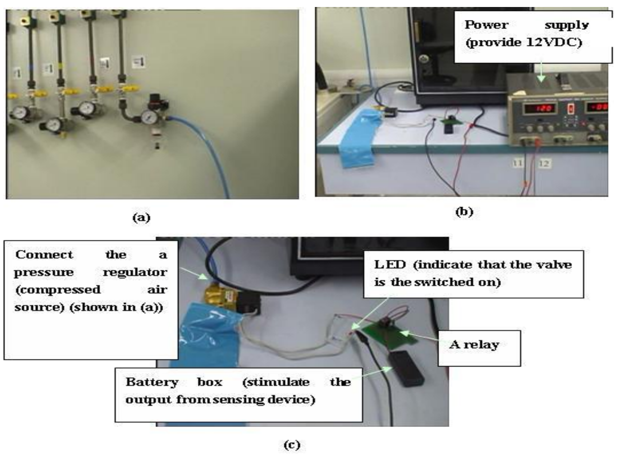

Fig. 3 Experimental setup of airbag system.

As shown in figure 3, we used a laboratory compressed air source with different pressures for our initial experiments. The compressed air acts as various CO_2 cylinders with different pressure. A solenoid valve SLG5404-04 (EMC Co. Ltd.) is used as a switch for the compressed air which acts as the inflator of the airbag system. The valve has response time as short as 15ms. We used a relay to deliver 12V from a power supply to the solenoid valve.

We modulated the compressed air source from 1 Bar to 6 Bars and used 5V as a switching voltage to open or close the solenoid valve.

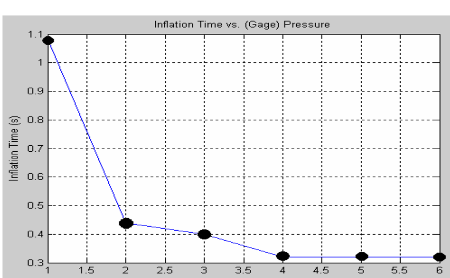

Fig. 4 Results of continuous inlet pressure V.S. inflation time.

Figure 4 shows the inflation time of the airbag under different inlet pressures. As shown, for any inlet pressure greater than 2 Bars, inflation time is less than 0.5 sec. For pressures from 4Bars to 6Bars, the inflation time can be limited to less than 0.3 second, which ensures the airbag can be deployed before a human falls to the ground. A regular fall takes 0.4-0.5 sec from start to finish, hence a pressure of 4 Bars is sufficient for an airbag action.

Ⅳ REAL TIME RECOGNITION OF FALLS

The motion sensing module can be used to recognize human motions, i.e., we could make it discriminate the falling-down state from other normal human motions. When falling is recognized, a trigger signal will be sent to a valve to open a airbag and the gas is released to inflate the airbags that reduces the force of impact when a person falls down to the ground.

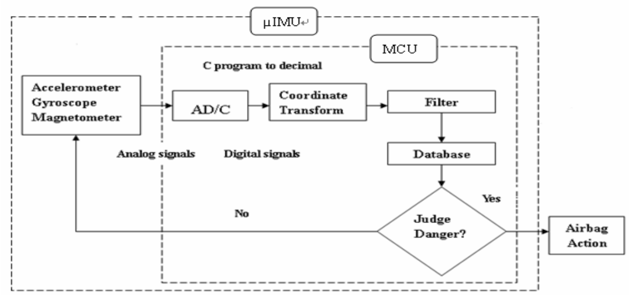

Fig. 5. Schematic chart of the µIMU system.

For independent motion recognition, the motion sensors work together with the MCU, as shown in figure 5. The MCU first converts the analog accelerations and angular rates into digital signals. Then, using special algorithms including coordinate transformation and filters, the system classifies the motion. For initial experiments, we transmitted all motion sensor data to a computer. After analysis, a reliable filter and recognition algorithm was developed and implemented entirely in the MCU, removing the need for an external computer.

We put µIMU on the left hip of a human and conducted two groups of experiments. The first is a hundred lateral falls since this is the most typical situation that is likely to cause a hip fracture. The second is one hundred other motions, including 10 running, 20 walking, 20 sitting, 20 squating, 10 stepping on stairs, 10 walking in an elevator and 10 jumping actions. The reason for selecting these motions is that they are commonly encountered motions. For the elderly, who seldom jump and run, we collected more sitting and squatting motion data. In addition, these motions are more similar to the motion during a fall. These experiments could then formulate a database for later SVM training and judgment. We can also discriminate falling from other motions directly from analysis of the original data.

A lateral fall of a human subject can be modeled as:

$$\frac{1}{6} ml^2 \omega^2 + \frac{1}{2} mgl \cos(\varphi) = \frac{1}{2} mgl \tag{1}$$

$$\omega^2 = \frac{3g}{l}(1 - \cos\varphi) \tag{2}$$

where l is the height of one's hip, ω is the angular rate when a person is falling, φ is the tilt angle when falling. A static fall is one for which the only energy supplied is gravity. During a fall, rotation is also observed and the angular rate is related to the angle that a person is tilting and the height of the center of mass of the person (equation 2). In static lateral fall experiments that we conducted,, the person was assumed to fall from a start where the angular rate is zero.

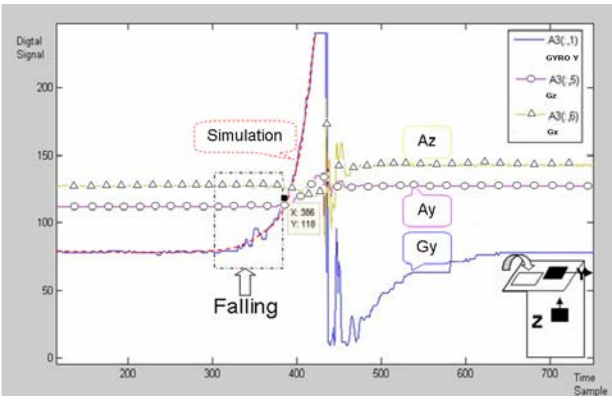

Fig. 6 Analasis for a lateral falling-down.

Figure 6 shows fall data recorded by the sensor module. One acceleration and 2 angular rates are not shown since for an idealized lateral falling motion, the only motion of the body is due to gravity. That is, the acceleration Y (Ay) and acceleration Z (Az) all change by 1-G during a fall. The angular rate in the lateral direction Gy will also change._We modeled the angular rate change during a fall using Equation 2, and the analytical results closely matched the experimental results (Gy) as shown in Figure 6. From the figure we can also see that accelerations due to gravity change only at impact and not at the beginning of a fall. This is because the person is first under a free-fall, and the body is effectively weightless during this period. Therefore, there is no change in the sensor signal before the body angle is larger than some value.

According to this observation, we programmed our microcontroller to compare the angular rate with a fixed threshold. When the angular rate value is larger than this value we send an activation signal to the airbag for inflation.

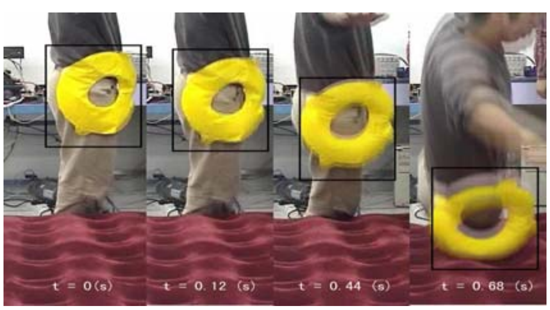

Fig. 7 A demostration of real time recognition of falling-down motion with inflation of airbag.

We set up a demonstration by connecting the µIMU and the airbag together. When a person is falling, the µIMU transmits a danger signal to the relay, and the relay drives the solenoid valve open and the compressed air will inflate the airbag, reducing the impact force of the fall. Figure 7 shows a successful demonstration of the human airbag system. The airbag was inflated just before the person falls to the ground.

V SVM TRAINING FOR FALL RECOGNITION

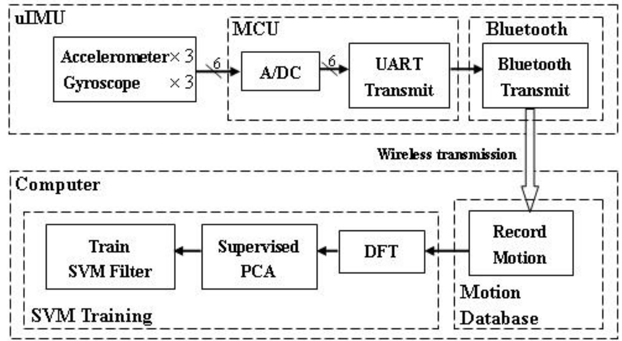

Fig. 8 Schematic chart of SVM training.

Although a simple angular rate threshold gives good results, false inflations can occur during normal physical activity. An SVM-based scheme using a host computer was tested to better distinguish between normal and falling motions.

As shown in Fig.8, the MCU first converts the sensor outputs to digital signals and then transmits the packed data signal sequentially via a Bluetooth module to a computer. Hundreds of recordings which included lateral falls, walking, running, sitting, walking up and down stairs and walking in elevators, were made to form a database for Support Vector Machine (SVM) training. After training, we selected the best features to form a classifier for falling-motion recognition.

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

(1) Set up a motion database of 'falling-down' and 'non-Falling-down' examples using the uIMU;

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

(3) SVM training (Support Vector Machine) to produce a classifier.

A. Database construction

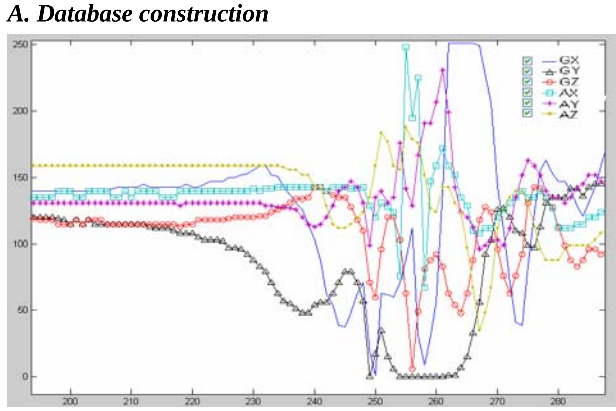

Fig. 9 Original motion data recording of falling.

As mentioned before, 200 recordings were made including 100 lateral falling-down and 100 other motions. They were all saved as text files having 6 dimensional entries of fall data for each recording. Since our sampling rate is 200 Hz, we record 3 accelerations and 3 angular velocities every 5 milliseconds.

Fig. 9 shows the original data of motion including 3D accelerations and rotation rates from one experimental trial. *GY* (triangles) is the angular rate of the pitch direction. We can judge when a fall-motion starts from the change of *GY. AZ* (circles) is 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 six sensors.

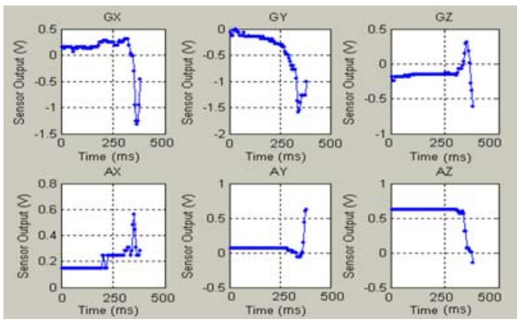

Fig. 10 Pure falling-down state cutting.

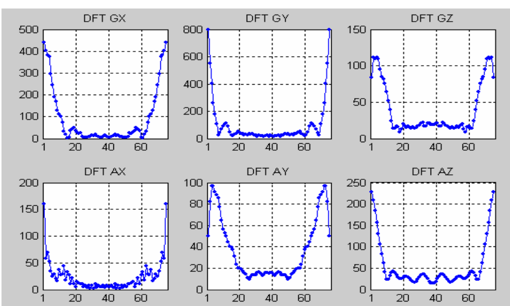

Fig. 11 DFT transform result V.S. frequency of falling.

An example of the motion data from the six sensors through this short duration (350ms) of motion is shown in Fig. 10. Fig. 11 shows the same data after a discrete Fourier transform (DFT) has been applied, changing the information to the frequency domain. One hundred fall-down experiments were done including different falling-motions and the experiments were also performed by two different people for construction of a realistic database.

B. PCA for feature selection

Principle Component Analysis (PCA) can be used to generate mutually uncorrelated features while packing most of the information in several eigenvectors. We use supervised PCA to generate features and select high-quality combinations for better recognition performance.

The method can be described 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 can be projected onto an axis extended by the corresponding eigenvector. By analyzing the distribution of the projected *2N* points, we can select the top M eigenvectors according to their eigenvalue to determine the number of dimensions needed to represent the training data.

M is the number of eigenvectors and *2N* is the total number of training samples. The original training data can be greatly reduced in dimensionality by representing the original 60 dimensional data as an M-dimension projection of the eigenvectors. Good approximations can be made using small values of M.

C. SVM scassifiers

The Support Vector Machine is a technique in the field of statistical learning theory [11]. Originally, SVM was developed for classification problems and was later 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 [12].

$$f(\bar{x}) = (\omega \cdot \Phi(\bar{x})) + \mathrm{b} \quad (\Phi : R^N \rightarrow F, \omega \in F) \qquad (3)$$

where *b* is a threshold. Thus, linear regression in a high dimensional (feature) space corresponds to nonlinear regression in the low dimensional input space R^N. Note that the dot product in (3 between ω and $\Phi(\bar{x})$) would have to be computed in this high dimensional space which is computationally expensive. A more efficient technique is to use a 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:

$$R_{reg}[f] = R_{emp}[f] + \lambda\|\omega\|^2 = \sum_{i=1}^{l} C(\mathrm{f}(\bar{x}_i) - \mathrm{y}_i) + \lambda\|\omega\|^2 \qquad (4)$$

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 functions, (4) can be minimized by solving a quadratic programming problem, which has a unique solution [12]. It can be shown that the vector ω can be written in terms of the data points:

$$\omega = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*)\Phi(\bar{x}_i) \qquad (5)$$

with α_i, α_i^* being the solution of the aforementioned quadratic programming problem [12]. 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 [13]. Taking (3) and (5) into account, we are able to rewrite the whole problem in terms of dot products in the low dimensional input space:

$$f(\bar{x}) = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*)(\Phi(\bar{x}_i) \cdot \Phi(\bar{x})) + b$$
$$= \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(\bar{x}_i, \bar{x}) + b \quad (6)$$

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

D. SVM training and fall recognition

We recorded 200 experimental results consisting of half 'falling-down' and half 'non-falling-down' data. Each result consisted of 6 arrays measured by the 6 sensors respectively.

We performed data pre-processing to filter noise and reduce dimension. For each experimental result, we performed a DFT of the 6 arrays respectively. We kept the first 10 coefficients of each DFT result. After 200 DFTs, we obtained a matrix of 200 rows and 60 columns, each row representing an experiment. Each has 6*10 numbers in the sequence *Gx, Gy, Gz, Ax, Ay, Az*.

We found that compressing the training data to 3 dimensions using PCA was sufficient to obtain good classification results. We randomly chose half of the data for SVM training and the other half was used for testing.

On the unseen testing data good results were obtained and the resulting system could classify the test vectors into 'falling-down' and 'non-falling-down' states without error.

Table 1. The coefficients of SVM classifier

c_0	-4.114032908	c_5	-0.000013017
c_1	0.029363568	c_6	0.000056986
c_2	0.009281220	c_7	0.000004560
c_3	0.004760046	c_8	-0.000013625
c_4	-0.000004642	c_9	0.000052657

The computation required for the SVM classifier is shown in Equation 7. The corresponding coefficients are shown in Table 1.

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

Although the training process is computationally expensive, after training, the computational requirements of the classifier are very small.

VI CONCLUSION

This paper presents a novel MEMS based human airbag system that is under development. A Micro Initial Measurement Unit (μIMU) for detection of complex human motions and recognition of falling-down motion is used, which can then be used to trigger the release of airbags. Experiments showed that our airbag system can achieve real-time recognition and fast response, which ensures that the airbags can be released before a human impacts the ground. The μIMU can also measure human motion in the form of accelerations and rotations in three dimensions. With a Bluetooth module, the small size unit can transmit experimental data to a computer for post-experimental data analysis. We also used SVM as a pattern recognition method for training of data transformed via a DFT and PCA. We have shown that selected eigenvector sets can classify 200 experimental data sets can be used to classify the eigenvectors into "non-falling-down" or "falling-down" categories without error.

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