Fall Detection by Embedding an Accelerometer in Cellphone and Using KFD Algorithm

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Summary
The fall is a risky event in the elderly people's daily living, especially the independent living, it often cause serious injury both in physiology and psychology. Wearable sensor based fall detection system had been proved in many experiments for its feasibility and effectiveness, but there remain some crucial problems, include: the people maybe forget to wear the clothes with micro sensors, which device standard should be selected between medical device standard and mass market standard, and how to control the false alarm probability to fit the individualized requirements. To deal with these problems, we think it is a reasonable design to combine micro sensors with an ambulatory daily using device which has a common network interface, and adjust the classification parameters via a remote server. In this paper, we embed a tri-axial accelerometer in a cellphone, connect to Internet via the wireless channel, and using 1-Class SVM (Support Vector Machine) algorithm for the pre-processing, KFD (Kernel Fisher Discriminant) and *k*-NN (Nearest Neighbour) algorithm for the precise classification. And there were 32 volunteers, 12 elders (age 60-80) and 20 younger (age 20-39), attended our experiments, the results show that this method can detect the falls effectively and make less disturbance to people's daily living than the general wearable sensor based fall detection systems.

Key words:
Accelerometer, Cellphone, Fall detection,1-Class SVM, KFD.

Introduction

The fall is a very risky factor in the elderly people's daily living, especially the independent living, it often cause serious physiological injury[1-4], such as bleeding, fracture, and centre nervous system damages. If the emergency treatments were not in time, these injuries may result in disability, paralysis, even death. And on the other hand, the fall also produces many psychological problems, e.g. fear of movement, worry about living independent, etc[5].

In order to find falls effectively and timely, many fall detection methods have been developed and shown their well performance[4, 6-8]. The current fall detection methods can be basically classified in three types[9]: video based, acoustic based and wearable sensor based system. The video based system means capturing the images of human movement via one or several vidicons, and then determining whether there is a fall occurred based on the variations of some image features (e.g. the moments, aspect ratio[10]). The acoustic based system means detecting a fall via the analyzing on the audio signals. In generally, this method is not well in precision, and is only selected as an assistant way to the other methods. The wearable sensor based system means embedding some micro sensors into clothes (also include girdle, cap, shoes, ornaments, etc.), to monitor the human activities in real-time, and find the occurrence of a fall based on the changes of some movement parameters[11]. As long as a person wear such a clothes, he will be monitored anywhere.

Because a vidicon is usually installed in fixed locations, but the human body is an ambulatory object, the wearable sensor based system is generally more suitable for fall detection than video based system.

Wearable technology is thought of one of the most important technologies on home tele-care and tele-rehabilitation in the near future, it has the advantages of continuity, low-cost, and easy to be used[12-14]. But for fall detection systems, there remain some crucial problems, include: 1) the people maybe forget to wear the clothes with micro sensors. The fall is an unexpected event, it usually does not appear for a long period (several moths or several years), and the wearable device will produce some uneasy feeling although that is slightly, so the people often lower his guard and forget wear the special clothes or device as time passed; 2) which device standard should be selected between medical device standard and mass market standard. If the device is made in medical device standard, that will be more reliable but higher cost, and the other standard means some weakness in reliability but lower cost; and 3) how to control the false alarm

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probability to fit the individualized requirements. That is a dilemma: if the false alarm probability is decreased, the miss alarm probability will be increased, vice versa. Because each person is in individual healthy condition and living environment, if we set a constant false alarm probability, that will result in the more risk of missing alarm to some people (e.g. the people with some equilibrium disorders), but the more disturbances to the other people (e.g. the elderly people in good health).

To deal with these problems, we think it is a reasonable design to combine micro sensors with an ambulatory daily using device which have a common network interface, increase the reliability via software redundancy designs, and adjust the classification parameters via a remote server which has a database about the users. Hence, we embed a tri-axial accelerometer in a cellphone, connect to Internet via the wireless channel, and set two servers (one master and one reserve) on the network.

The cellphone has been becoming a daily using device, the function of talking and short message can play a role of remaindering the users not forget taking this device. The cellphone also provides us a common technology platform for connecting to Internet, let us can easily adjust the device parameters and acquire information support. But the cellphone is in public communication networks, which does not very stable, we alleviate this shortage via the ways of re-sending and multi-point transmitting.

The movements of the accelerometer in our system are quite different from the general wearable sensor based systems, this brings us some complexity in computing, so we developed a two-levels algorithm, i.e. using 1-Class SVM (Support Vector Machine) algorithm to extract the doubtful fall data from the inputs, and then realize the precise classification via KFD (Kernel Fisher Discriminant) and *k*-NN (Nearest Neighbor) algorithm.

We gathered about 1100 samples, and there were 32 volunteers, 12 elders (age 60-80) and 20 younger (age 20-39), attended our experiments, the results show that our method can detect the falls effectively and make less disturbance to people's daily living than the general wearable sensor based fall detection systems.

2. Methods

2.1 Hardware and System Structure

The experiment system consists of two computers and a cellphone with a box affixed, as shown in Fig.1. The computers are used as remote servers. Inside the box, the circuit includes a tri-axial accelerometer (TA), a single-chip modem, a MCU (Micro-controller Unit), and some peripheral components.

The TA, "MMA7260Q", manufactured by Freescale™ Semiconductor, is a low-g micro-machined resistance accelerometer with the volume 4*4*1mm, single power supply 2.2V-3.6V. And this sensor has four measuring ranges: 1.5g, 2g, 4g and 6g, where we choose the 6g. When the power supply is 3.3V, the typical current is 0.5mA, and the typical sensitivity is 800mV/g. The outputs are three mutual perpendicular accelerations a_x, a_y, and a_z. When in static, the vector sum of a_x, a_y, and a_z is the acceleration of gravity. Here, the sample rate we selected is 128 points per second.

The single-chip modem, "MSM7512BRS", produced by OKI Semiconductor, is a 1200bps half Duplex ITU-T V.23 modem. The package type is DIP16-P-300–2.54, and the power supply range is 3V to 5V. The power consumption is 25mW Typ. in operating mode, and 0.1mW Max. in power down mode.

The MCU, "PIC18F2455", is a production of Microchip Technology Inc. The main features of this chip include: 24KByte flash program memory , 2048Byte SRAM and 256Byte EEPROM data memory, 10-Bit A/D converter, 8 * 8 single-cycle hardware multiplier, and 3.0-5.5V power supply.

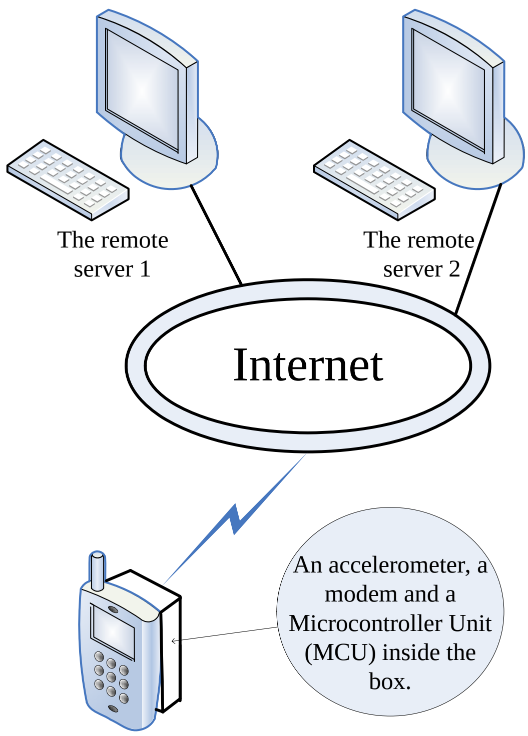

Fig. 1 The system structure

The circuit and the cellphone compose a fall detector: the acceleration signals are transformed into digital signals via A/D conversion, and then analyzed by the MCU. If a fall is determined, the MCU will send a UDP (User Datagram Protocol) package to a remote server via the wireless channel. Here, server 1 is the master server, and server 2 is the reserve server. The fall detector sends the data package to server 1at first, if fail, it will send the data package to server 2. And on the other hand, the MCU can also receive the instructions and data from either of the servers.

2.2 Software

The software includes the MCU program, the server program and a database. For the MCU, there are a ISR (Interrupt Service Routine) and a main program. The ISR completes the works of data collection and A/D conversion, and keeps a 192*3Byte-length FIFO (First In First Out) sequence to record the input data. At every end of a second, the ISR puts the recording data into an input buffer (InBuff) and sets a 1_second sign to notice the main program to catch the data. If the main program could not catch the recording data in time, the InBuff will be updated. At the same time, the ISR maintains a timer to give a communication span to avoid the overload of channel.

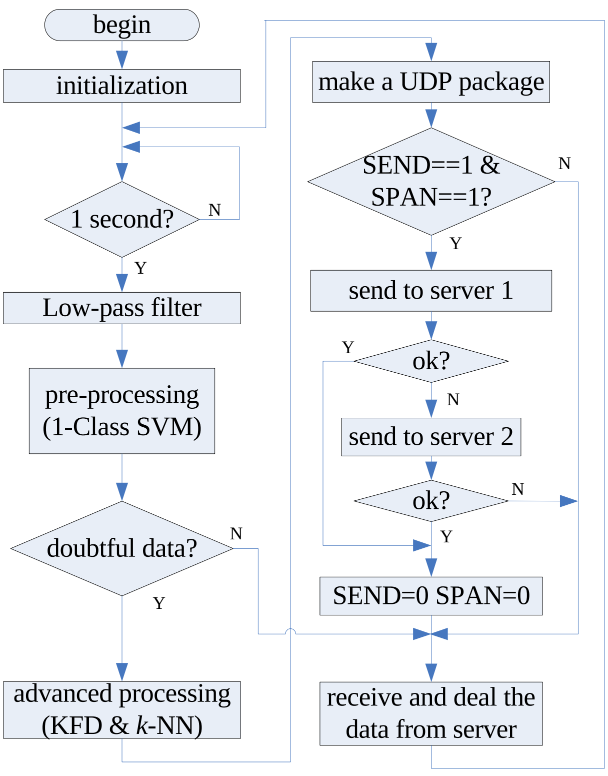

Fig. 2 The flowchart of the main program in MCU (where SPAN is the sign related to the communication span, the ISR set it to 1 after it had been 0 for 15 seconds)

Fig.2 shows the flowchart of the main program in MCU. The 1_second sign is checked at first, if it is valid, the data in InBuff will be transferred to a calculation buffer (CalBuff), and the 1_second sign cleared, then a low-pass filtering algorithm is performed to get rid of the noise. In the next step, a 1-Class SVM-based algorithm is carried out to evaluate whether the data is similar to a fall in high-probability, and then the doubtful data will be classified via the KFD and *k*-NN algorithm. If a fall is confirmed, the MCU will make a UDP package (based on Ipv4 format), set it in an output buffer (OutBuff), and set an upload-sign valid (SEND=1). When the main program finds SEND==1, it will transmit the UDP package to either of the server. If the communication succeeds, SEND will be cleared. Hence, once the communication failed, SEND is still 1, the UDP package will be sent repetitively (here we set a upper limit of 100 times, and the transmitting span is 15 seconds).

The sever program is developed in Java, and the database is MySQL3.1. The functions of sever program include alarm display, parameter management, user interface and database management. The two server run the same program, but the priority is different And each server has its own database, the two databases are enantiomorphous. The content of the database involves the user's individual information and the values of classification parameters. We can realize the individual parameter control (especially the control of false alarm probability) based this database.

Because UDP is not a credible protocol, here we increased the reliability via acknowledgement mechanism, i.e. once the MCU received a package, it will reply a acknowledgement package to the server, vice versa.

2.4 Fall Analysis

In some cases, the fall does not cause serious results, e.g. the subject fall down and re-standing quickly. We call this type of fall non-damaged-fall, and consider it is not necessary to trigger an alarm. We call the other types of fall as damaged-fall. Here, "fall detection" means finding the damaged-fall.

We denote a as the norm of the vector sum of the outputs from the TA, i.e. $a = |\boldsymbol{a}_x + \boldsymbol{a}_y + \boldsymbol{a}_z|$. In general, to a damaged-fall, there are three steps in turn: daily activities, falling and a period of motionless (or only a little motion). The changes of acceleration in the first step are random, the falling will cause acutely varieties in acceleration and generally be completed between 0.4-0.8 second [4], and the motionless period will last for several seconds or more with a near the acceleration of gravity. So we detect a at first, if it nears $|g|$ in a period of one second, we will consider the subject in motionless, then we backdate the data for 1.5 seconds and take the data section (192 points) as the input sequence, then we carry out some classification algorithms to determine if there really exists a falling course.

In the current fall detection systems [1-9], the accelerometers are bind to human body (in generally bind to trunk), there exists the fixed angle relation between the sensor and the human body, the fall can be detected by monitoring the angle varieties of the human body [1-3, 9](e.g. from vertical to horizontal quickly), or by some intelligent algorithms based on a set of lower dimensional features [8]. But in our system, the movements of the accelerometer are more complex than the former, for instance, 1) one holds the phone and turn his hand, 2) one throws his phone onto a sofa, 3) one put the phone in his pocket quickly. In these cases, the varieties of acceleration are often very similar to a really fall and some high-intensity human daily activities.

Hence, we design our computing in two steps: the pre-processing and the advanced processing. In the former, we use 1-Class SVM algorithm to extract the doubtful data based on some lower dimensional features, and in the latter, we use KFD and *k*-NN algorithm realize the precise classification based on high dimensional features.

2.5 Pre-processing

Fall detection is a binary decision problem, if we denote the fall data as positive samples and the non-fall data negative samples, we will face such a situation: the positive samples have a lot commonness while the negative samples are diversified (or we can say it is random). In other words, it is hard to capture enough negative samples for training the classifier. In this case, 1-Class SVM is a nice choice. 1-Class SVM mapping all the samples into a high dimensional feature space by using of a kernel function, then it searches a minimal hypersphere to evolve all the positive samples inside, and uses a group of slack variables to realize the trade-off between the radius of the hypersphere and the number of the samples which outside the hypersphere[8, 15]. This algorithm ascertains the decision interface mostly based on the positive sample set, and the number of negative samples could be less.

We developed a 1-Class SVM based algorithm [8], the feature space is six-dimensional and the results show that it is well in distinguishing falls from lower-intensity daily activities, but some weak in distinguishing falls from high-intensity daily activities. So we use the method in conference [8] as pre-processing to extract the doubtful data from the daily movement acceleration sequences. Here the input is the 192-points sequence that introduced in section 2.4, and we adjust the slack variables to ensure 99% of real fall samples can be classified into the doubtful data set.

2.6 Kernel Fisher Discriminant

After the pre-processing, we use KFD algorithm to realize the optimal separability for the doubtful data

The Fisher Discriminat transforms a classification problem from high-dimensional pattern space to lower-dimensional feature space via a group of projection operations, and the projection result has the optimal separability[16, 17]. To dichotomy problems, in linear case, this can be achieved by maximizing the Rayleigh coefficient [16]:

$$J(w_{opt}) = \arg\max_{w}\left(\frac{w^T S_b w}{w^T S_w w}\right) \quad (1)$$

where w is a linear transform, S_b is the between class variance, S_w is the within class variance

$$m_k = \frac{1}{|I_k|}\sum_{i\in I_k} x_i, \quad k=1,2$$

$$S_w = \sum_{k=1}^{2}\sum_{x\in\omega_k}(x-m_k)(x-m_k)^T$$

$$S_b = (m_2-m_1)(m_2-m_1)^T$$

here m_k is sample mean of the *k*th class, I_k is the index set for the *k*th class, and $|I_k|$ indicates the number of vectors in the *k*th class.

In nonlinear case, this problem is mapped to a kernel feature space, and the Fisher Discriminant becomes KFD [16-21], i.e. via the mapping ϕ:

$$\phi: \quad R^n \to F, \quad x \to \phi(x)$$

the items in equation (1) become w^ϕ, S_b^ϕ, S_w^ϕ,and m_k^ϕ, respectively, where

$$w^\phi = \sum_i \alpha_i \phi(x_i) = \phi(x)^T\alpha$$

$$m_k^\phi = \frac{1}{|I_k|}\sum_{i\in I_k}\phi(x_i), \quad k=1,2$$

And equation (1) itself is mapped into the formulation:

$$J(\alpha_{opt}) = \arg\max_{w_\phi}\left(\frac{{w_\phi}^T S_b^\phi w_\phi}{{w_\phi}^T S_w^\phi w_\phi}\right) \quad (2)$$

$$= \arg\max_{\alpha}\left(\frac{\alpha^T\phi(x)S_b^{\phi}\phi(x)^T\alpha}{\alpha^T\phi(x)S_w^{\phi}\phi(x)^T\alpha}\right)$$

$$= \arg\max_{\alpha}\left(\frac{\alpha^T\phi(x)(m_2^{\phi}-m_1^{\phi})(m_2^{\phi}-m_1^{\phi})^T\phi(x)^T\alpha}{\alpha^T\phi(x)(\sum_{i=1}^{2}\sum_{x\in\omega_i}(\phi(x)-m_i^{\phi})(\phi(x)-m_i^{\phi})^T)\phi(x)^T\alpha}\right)$$

$$= \arg\max_{\alpha}\left(\frac{\alpha^T M\alpha}{\alpha^T N\alpha}\right)$$

where

$$\mu_k = \phi(x)m_k^{\phi} = \frac{1}{|I_k|}\phi(x)\sum_{i\in\omega_k}\phi(x_i) = (1/|I_k|)K1_{I_k},$$

$$\mu = \mu_2 - \mu_1,$$

$$M = \mu\mu^T, N = KK^T - \sum_{k=1}^{2}|I_k|\mu_k\mu_k^T$$

$$K_{ij} = (\phi(x_i)\cdot\phi(x_j)) = k(x_i, x_j)$$

here 1_{I_k} means the value of an element are 1 if it belongs to I_k , otherwise 0.

The projection of a test input x will be

$$(w^{\phi}\cdot\phi(x)) = \sum_i \alpha_i k(x_i, x) \quad (3)$$

the coefficient vector α can be determined by solving an equivalent convex quadratic programming problem [17]. Here we select RBF (Radial Basis Function) as the kernel function

$$k(x_i, x_j) = \exp(-\frac{\| x_i - x_j \|^2}{\sigma^2}) \quad (4)$$

The value of σ is determined by searching, where firstly we implement the draft search in logarithmic space, i.e. let $\log(\sigma^2)\in[-3,0]$, divide the closed interval into 8 equal parts, selected the minimal value in every parts to train, and choice the optimal part denoted as $Span1$. Then we carry out a finely search in linear space, i.e. transform $Span1$ in linear space $\sigma^2 \in Span2$, divide $Span2$ into 32 equal parts, also select the minimal value in every parts to train and reserve the optimal σ^2.

2.7 Classification and the Control of False Alarm Probability

After the projective operation of KFD, we use k-NN algorithm to realize the classification. For an input test vector, the decision function is:

$$if \quad k_1\cdot p_c\cdot\frac{n_2}{n_1}\cdot\sqrt{N_{\omega 2}/N_{\omega 1}} \ge k_2, \quad k_1 + k_2 = k \quad (5)$$

$$then \quad x\in\omega_1 \quad , \; otherwise \quad x\in\omega_2$$

where the first class ω_1 indicates the fall samples, the second class ω_2 the non-fall samples, and k is the number of the nearest neighbors, k_1 is the number of the nearest neighbors belongs to ω_1, k_2 is that of ω_2. The n_1 is the number of the samples belongs to ω_1 , n_2 that of ω_2. $N_{\omega 1}$ is the within class variance of ω_1 in the feature space, and $N_{\omega 2}$ that of ω_2. And p_c is a coefficient that is used to control the false alarm probability, where the value of p_c is in direct proportion to the false alarm probability. The individualized p_c is stored in the database, and can be transmitted to the MCU, thus we can achieve the individualize false alarm probability control.

The value of k is also determined by searching, where we let $k\in\{11, 13, \ldots, 51\}$, then examine every vector in the training set for each k, and select the optimal ones.

3. Results

We arranged the experiments on 6 categories: 1) ordinary daily activities, include walking, jogging, sitting or groveling down at normal speed, etc.; 2) lower-risk fall down, the subjects fell down on the plane with soft cushion; 3) high-risk fall down, the subjects fell down on the hard plane, stairs and slope; 4) critical movement, the subjects did fleet movements that are some alike falling down, e.g. lay prone on the ground quickly, sat down heavily; 5) high-intensity daily activities, there were some acute daily activities, e.g. running, jump and gymnastics; 6) special movement, include holding the cellphone in hand and do some activities (e.g. turning the hand, tremble), throwing the cellphone on a sofa, etc.

In the former 5 categories, the cellphone was taken in the pocket of clothes, or hanged on the neck. Because the fall situation is dangerous to human body, especially to the elderly, so the elderly volunteers only attended category 1 and 6, the younger volunteers attended all the categories except category 3, while category 2 and a part of category 1 were implemented with a dummy. For the dummy, the cellphone was put in a pocket that bound to the low back.

Fig. 3 The falls demoed by volunteer (the two upper images) and by a dummy (the two lower images)

There were 32 volunteers, 12 elders (age 60-80) and 20 younger (age 20-39), attended our experiments. Fig.3 shows two fall experiments belong to category 2 and 3, respectively. We gathered about 1100 samples, randomly selected the 2/3 for training and the other for testing, as shown in in table.1.

Table 1: The distribution of the samples

category	1	2	3	4	5	6
total samples	102	240	178	200	98	276
samples for training	68	160	119	134	66	184
samples for test	34	80	59	66	32	92

In the pre-processing, we have 279 fall samples and 452 non-fall samples for training. The aim is to classifying 99 percent fall samples in positive sample set. In RBF based 1-Class SVM, there are two important parameters $v \in (0,1)$ and σ^2, the former is a coefficient that controls the volume of the hypersphere and the number of the outliers, and the latter is the variance of the RBF. The searching operation is similar to the method in conference [8], and we get the optimal parameters of v=0.43, and $1/\sigma^2$=105. The distribution of the samples in doubtful data set is show in table.2, and we found 45 support vectors in the 1-Class SVM model.

In the advanced processing, we use the doubtful data set to train the model, and get the optimal parameters of σ^2=0.012 and k=21. The test results are shown in table.3, and the mean ratio of correctness r_m is 93.3 percent, where

$$r_m = \frac{1}{N}\sum_i r_i \tag{6}$$

here N=6 is the number of the categories, r_i is ratio of correctness of the ith category.

Table 2: The distribution of the samples in doubtful data set

category	1	2	3	4	5	6
samples	0	157	118	43	19	72

Table 3: The test result

category	1	2	3	4	5	6
correct	34	78	57	61	27	82
incorrect	0	2	2	5	5	10
ratio of correctness (%)	100.0	97.5	96.6	92.4	84.4	89.1

4. Discussion

In theory, 1-Class SVM can extract the real fall data from the inputs, but that needs a high-dimensional features set and the related a great quantity of samples. It is difficult to get a large number of fall examples, in fact, a volunteer would be very tired after falling 5-10 times in our experiments, and at the same time we could hardly imitate some types of fall very truly, e.g. sliding and fall on stairs, fall down while somebody standing on a chair, etc. In the other hand, if we use KFD to deal the original input vector directly, because the negative sample set can only involve a little part of human daily movement, we would not get an available mean vector of the non-fall data. This is why we adopt the two steps computing.

Most of the current wearable sensor based system belongs to orientation-changed detection algorithm, they think connotatively that the tilt degree of human body will be changed significantly when a fall occurred, but that's not always true, e.g. in Fig.4, a person slide down and sitting on the ground, or the person fall down when he bow to pick something on the ground, the tilt degrees will be changed slightly. Thus, these algorithms have a lot of "blind areas", but our method has no this shortage.

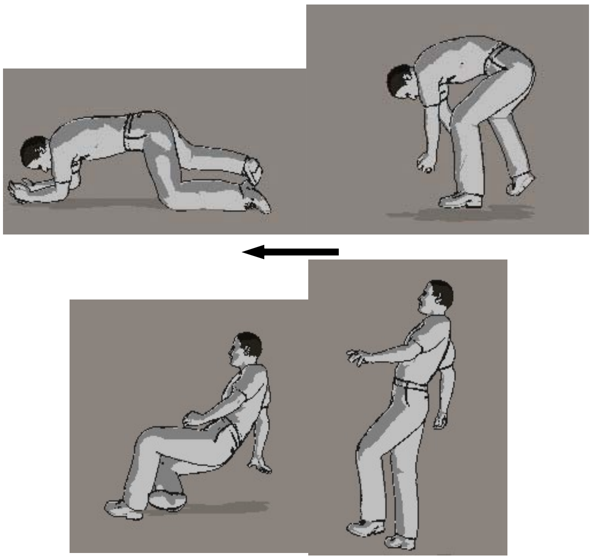

Fig. 4 Two examples of fall without acutely changes in body tilt (observing the position near belly button, the upper images shows a course of horizon-horizon, the lower vertical-vertical)

Because our aim is to detect fall, most of the non-fall samples we selected are basically more similar to falls than the other daily activities (e.g. cooking, sleeping). In other words, the probability of fall in our sample set is higher than that in daily living.

Compared to the simplex 1-Class SVM algorithm in conference [8], this two-step computing is more precise. We used the 1-Class SVM algorithm to train and test, and the mean correct ratio is 84.6 percent.

5. Conclusion

To design a long-term ambulatory monitoring system on human movements, it is necessary to consider several factors synthetically, include the reliability, cost, security, communication and the less disturbing to users. The cellphone has been a device of daily use, in general, if we embed some micro instruments inside, it can still well fit the latter 4 requirements, and the problem of reliability descent could be avoided or alleviated via some intelligent processing. Thus, the combine of TA, cellphone, Internet and pattern recognition algorithms can realize the fall detection effectively and unobtrusively.

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