Expert Systems with Applications 37 (2010) 7174–7181

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A fall detection system using k-nearest neighbor classifier

Chien-Liang Liu *, Chia-Hoang Lee, Ping-Min Lin

Department of Computer Science, National Chiao Tung University, 1001 University Road, Hsinchu 300, Taiwan, ROC

A R T I C L E I N F O

Keywords:
Artificial intelligence
Machine learning
*k*NN
Fall detection

A B S T R A C T

The main purpose of this paper is to use off-the-shelf devices to develop a fall detection system. In human body identification, human body silhouette is adopted to improve privacy protection, and vertical projection histograms of the silhouette image and statistical scheme are used to reduce the effect of human body upper limb activities. The *k*NN classification algorithm is used to classify the postures using the ratio and difference of human body silhouette bounding box height and width. Meanwhile, since time difference is a vital factor to differentiate fall incident event and lying down event, the critical time difference is obtained from the experiment and verified by statistical hypothesis testing. With the help of the *k*NN classifier and the critical time difference, a fall incident detection system is developed to detect fall incident events. The experiment shows that it could reduce the effect of upper limb activities and the system has a correct rate of 84.44% on fall detection and lying down event detection.

1. Introduction

During the 20th century, the US population under age 65 tripled, but those who were 65 and older increased by a factor of 11. It is apparent that the proportion of older people is rising. About 1 in 8 Americans were elderly in 1994, but about 1 in 5 would be elderly by the year 2030 (Bureau, 2008). As with the great progress of medical technology, many countries are facing the issue of aging society, so there will be a lower proportion of people of working age available both to fund and to provide the necessary levels of care. Meanwhile, the problem comes after this issue is huge nursing cost and both of them influence our life now. Therefore, the demand for developing home surveillance systems is rising.

It is shown in National Center for Health Statistics (2000) and DA and JA (2001) that more than one-third of adults ages 65 and older fall each year. Falls are the leading cause of fatal and nonfatal injuries for people aged 65 and older. For adults 65 years old or older, 60% of fatal falls happen at home, 30% occur in public places, and 10% occur in health care institutions (GS, 1988). Recently, a lot of fall detection systems and posture classification systems have been developed to detect fall incidents (Anderson, Keller, Skubic, Chen, & He, 2006; Bramberger, Doblander, Maier, Rinner, & Schwabach, 2006; Cucchiara, Grana, Prati, & Vezzani, 2005; Juang & Chang, 2007; Miaou, Sung, & Huang, 2006; Nasution & Emmanuel, 2007; Tabar, Keshavarz, & Aghajan, 2006; Tao, Turjo, Wong, Wang, & Tan, 2005). Instead of using specially designed sensors and circuitry (Noury et al., 2000; Tamura, Yoshimura, Horiuchi, Higashi, & Fujimoto, 2000), the purpose of this study is to focus on using off-the-shelf devices to develop a surveillance system to detect fall incidents. The motives of our work arises from the fact that current home surveillance system is quite expensive and most people could not afford to buy one. Meanwhile, computer and web camera equipments are popularized recently and it will be of great help if these equipments could be used to provide surveillance service.

In essence, fall detection includes two main tasks: human body identification and fall incident detection. Identifying moving objects from a video sequence is a fundamental and critical task in many computer-vision applications such as video surveillance and traffic monitoring systems. Practically, video surveillance system may cause privacy threat to those who use the system, so human body silhouette is adopted here to improve privacy protection. Since human body silhouette has removed most of human body features, human body identification is prone to be effected by human actions. For example, people in the indoor may stretch out their hands to fetch and that may affect human body posture identification. Pixels projection and statistical analysis are used to reduce the effect.

The *k*-Nearest Neighbor (*k*NN) classifier (Duda, Hart, & Stork, 2000) is adopted to classify user's activities based on the features. In *k*NN classification algorithm, the number of classes and feature selection will be key factors. *k*-fold cross-validation is adopted to choose the best *k* value (the number of classes), and statistical analysis is used to facilitate feature selection. Practically, lying down event and falling down event are so similar that it may often lead to misjudgment. According to our experiments, the time difference between time of lying posture and temporary posture could be used to differentiate these two activities. In this paper,

* Corresponding author. Tel.: +886 3 5131503; fax: +886 3 5734935.
E-mail address: clliu@mail.nctu.edu.tw (C.-L. Liu).

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doi:10.1016/j.eswa.2010.04.014

the critical value of time difference is determined by experiments and verified by statistical hypothesis testing. According to the experiment, the system could successfully detect fall incident and lying down event with a correct rate of 84.44%.

The rest of the paper is structured as follows. In Section 2 a survey of related researches on indoor monitoring and surveillance is presented. Section 3 describes the system framework which includes the human body identification and fall incident detection. In Section 4, several experiments are conducted to show that it works well on fall incident detection. Finally, Section 5 contains the conclusion.

2. Preliminary

Rapid advances in the technologies of image sensors and embedded processors enable the inclusion of vision-based nodes in various smart environment applications (Bramberger et al., 2006). Various studies on the use of accelerometer signal for posture classification have been reported. Tabar et al. (2006) proposed a wireless sensor network employing multiple sensing and event detection modalities for smart home monitoring applications. The fall alert is broadcasted by the user badge which is carried by the user when the accelerometers on the badge record a significant change in their measured signal. Meanwhile, image processing is used to analyze the situation and determine the user's posture when alerts happen. Miaou et al. (2006) proposed to use MapCam (omni-camera) to detect the fall of the elderly. Moreover, the personal information of each individual is considered in the processing task and the MapCam could capture 360° sense simultaneously.

Tao et al. (2005) proposed an intelligent video surveillance system to detect human fall incidents for enhanced safety in indoor environments and the feature they use is the aspect ratio of the moving object's bounding box. The system proposed by Tao et al. (2005) consists of two main parts: a vision component which can reliably detect and track moving people in the view of a camera, and an event-inference module which parses observation sequences of people features for possible falling behavioral signs.

Anderson et al. (2006) adopted the width to height ratio of the silhouette bounding box and the off-diagonal term from the covariance matrix as the features to determine whether fall incident occurs. The bounding box width to height ratio indicates whether the silhouette is larger in the vertical plane versus the horizontal plane. When the subject is standing, the width to height ratio is small. Meanwhile, when the subject is on the ground, the width to height ratio becomes much larger. These features need to be extracted from the silhouette to train and perform classification with HMMs for temporal pattern recognition.

In practice, privacy should be protected when designing fall detection systems. Currently many fall detection systems adopt silhouette to remove most of the human body features and human body identification will be prone to be effected by human actions. Therefore, it is necessary to reduce the effects of such actions. Besides, lying down and fall incidents events are similar and the system should be able to differentiate these two activities to avoid false alarms. These existing fall detection schemes (Miaou et al., 2006; Nait-Charif & McKenna, 2004; Tao et al., 2005) are unable to differentiate between real fall incident and an event where the person is simply lying without really falling (Nasution & Emmanuel, 2007).

3. System architecture

The falling detection system in this paper consists of two main parts: human body identification and fall incident detection. The objective of the human body identification is to identify human body and extract useful features from human body images. Meanwhile, fall incident detection will make use of these features to determine whether fall incident is taking place. Fig. 1 shows the system architecture in this paper. The input is the video image frames that are obtained from web camera. Video surveillance system may infringe privacy to those who use the system, so human body silhouette is adopted to improve privacy protection and several image-processing techniques are used to identify the object and to smooth noises. Feature selection is commonly used in machine learning applications for building robust learning models. Silhouette of the human body removes most of the human body features, so upper limb activities may affect the identification result and it is necessary to reduce the effects of such actions. The *k*NN classification scheme is used to perform postures classification, and 450 sample data is used as training data to build the training model. Finally, fall incident detection is achieved by fall incident detection flow.

3.1. Human body identification

As mentioned above, moving objects should be identified from the videos for further analysis. Frame differencing approach, which is low-complexity, is adopted to identify human body. Fig. 2(a) shows the image captured from the camera and Fig. 2(b) shows the human body identification result.

3.2. Image processing

The human body image extracted from moving object may contain noises, so additional process is required to eliminate the noises. Mean filter, which could soften an image by averaging surrounding pixel values, is adopted to make the image more smooth.

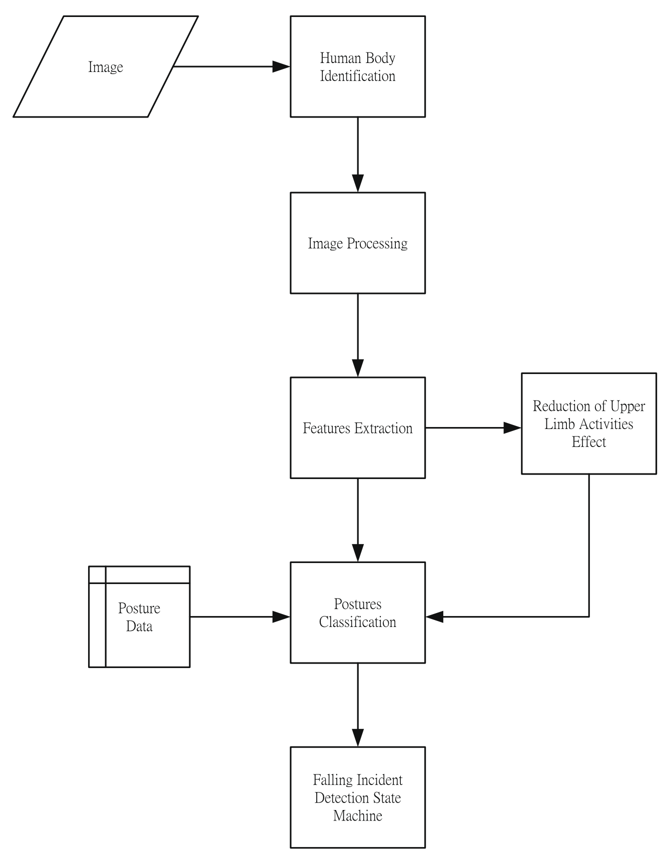


Fig. 1. System architecture.

(a) Image Frame From The Camera (b) Human Body Identification

Fig. 2. Video frame extraction from video and identification of the human body.

As shown in Fig. 3, each pixel surrounding the target is assigned the same weight and the average of the pixels is assigned to the target.

The gray-scale image will be transformed into binary image for further process, and thresholding is a method which could transform a gray-scale image into binary image (Shapiro & Stockman, 2001). Binary images are images whose pixels have only two possible intensity values. They are normally displayed as black and white. Numerically, the two values are often 0 for black, and either 1 or 255 for white.

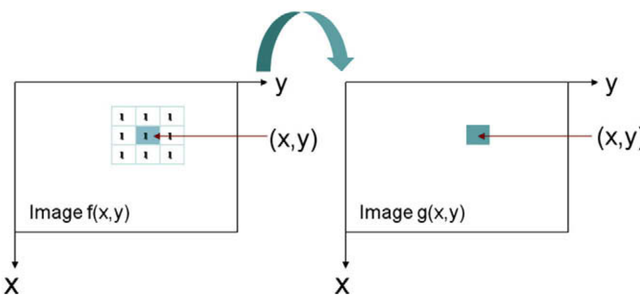


Fig. 3. Mean filter.

$$\begin{pmatrix} 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&1&1&1&0\\ 0&1&1&1&0&1&0&1&0\\ 0&0&1&0&0&0&1&1&0\\ 0&1&1&0&1&0&0&0&0\\ 0&0&0&1&1&0&0&0&0\\ 0&0&0&0&0&0&0&0&0 \end{pmatrix} \quad \begin{pmatrix} 0&0&0&0&0&0&0&0&0\\ 0&0&0&0&0&3&3&3&0\\ 0&1&1&1&0&3&0&3&0\\ 0&0&1&0&0&0&3&3&0\\ 0&1&1&0&2&0&0&0&0\\ 0&0&0&2&2&0&0&0&0\\ 0&0&0&0&0&0&0&0&0 \end{pmatrix}$$

Fig. 4. Connected components labeling using four-connected neighbor.

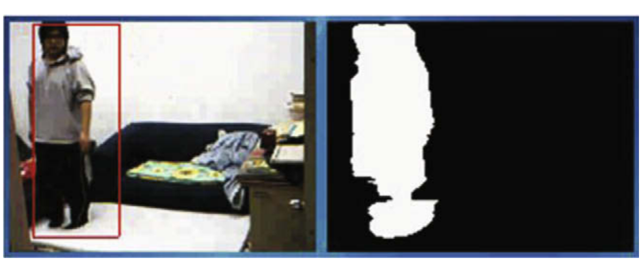


Fig. 5. Human body bounding box and its silhouette.

In addition to frame differencing, mean filter, and image thresholding processes, connected component labeling, which scans an image and group its pixels into components based on pixel connectivity, is used to capture the meaningful region in this paper. An arbitrary point on the image is marked as connecting objects and an unique number is assigned to all the connecting pixels that form four-neighbors to represent that they connect to each other. Once an unmarked pixel is discovered, a new number will be assigned to the pixel. The above process will repeat until all the pixels of the image have been marked. For each non-zero pixel, its four-neighbors will be checked, and if non-zero pixels are found, they will be at the same group and one number will be assigned as shown in Fig. 4.

3.3. Features selection

After the above image-processing steps are performed, the image of human body silhouettes would be obtained. In essence, although human body silhouette could protect user's privacy, human body silhouette also removes most of human body features. As shown in Fig. 5, the human body silhouette could not reveal personal information except the height and width of the silhouette.

In general, indoor activities include walking, sitting, standing, and lying etc. In this paper, the indoor activities are divided into three categories: standing posture, temporary posture and lying down posture. As shown in Fig. 6, aspect ratios of moving object's bounding box in standing posture and lying down posture represent two extreme values in indoor activities, while the temporary posture represents all other postures whose aspect ratios of moving object's bounding box are located between these two values. For example, temporary posture includes sitting, bending, and squatting postures etc.

Nasution and Emmanuel (2007) proposed to use horizontal and vertical projection histograms of segmented foreground and angle between last standing posture with current foreground bounding box as feature set for the task. Since projection histogram of lying toward the camera is closer to bending, lying toward the camera may be detected as bending. Nasution and Emmanuel (2007) proposed a modified classifier to improve the

Fig. 6. Standing, sitting, and lying postures.

detection of lying toward the camera, but that will need to store and update the bounding box information of the last detected standing posture all the time. Instead of using horizontal and vertical projection histograms and angle as feature set, the ratio of bounding box height and width and the difference of bounding box height and width are adopted as the system features in this paper. Fig. 7 shows the feature space result of experiment when adopting these new features.

3.4. Reduction of upper limb activities effect

As mentioned above, human body silhouette removed most of human body features, so height and width of human body silhouette are adopted as the features of fall incident detection in many studies. However, people may stretch out their hand to fetch something in the indoor environment and these activities may lead to incorrect measurement of the width of human body silhouette image. Therefore, it is necessary to reduce the influence of upper limb activities to obtain an approximate width value which is close to the original one. In this paper, we propose to use vertical projection histograms of the silhouette image and adopt statistical analysis to reduce the influence. Fig. 8 shows the projection result.

As shown in Fig. 9(a), the bounding box of the human body will change when the person stretch his hand and the vertical projection histograms of the silhouette image will produce a peak in the distribution curve. The individual mean and standard deviation are calculated, and a new value will be used to replace the original extreme value which is over threshold value and the threshold value is determined by Eq. (1). This procedure performs well to eliminate the effect of upper limb activities. Fig. 9(b) shows the result of eliminating upper limb activities after using this approach. The peak section will be reduced when compared with the original curve

$$threshold = 3 * \sigma + \mu. \quad (1)$$

3.5. kNN classifier for human body postures classification

The *k*-nearest neighbor (*k*NN) classifier (Duda et al., 2000), a supervised machine learning technique for learning a function

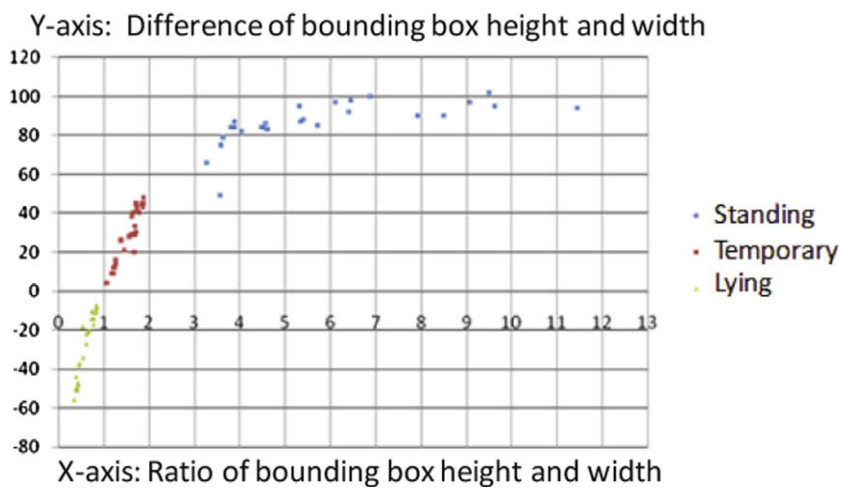


Fig. 7. Feature space of sample data.

Fig. 8. Project bounding box image pixels onto *Y*-axis.

(a) Project Pixels in Bounding Box to Y-axis without Reduction

(b) Project Pixels in Bounding Box to Y-axis with Reduction

Fig. 9. Image captured from video and silhouette of the human body.

from training data, classifies objects based on closest training data in the feature space. In order to identify neighbors, the objects could be represented by position vectors in a multidimensional feature space, and different distance measures have been proposed in the literature. Euclidean distance is used in this paper to represent the distance between the objects.

As described above, the system in this paper divides the indoor activities into three categories: standing posture, temporary posture, and lying posture, respectively. In this paper, 450 human body postures are collected for experiment, and each category contains 150 samples. In essence, a point in the space is assigned to the class c if it is the most frequent class label among the k nearest training samples, so the parameter k plays an important role in kNN classification.

In essence, kNN classifier should determine the parameter k in advance and the best choice of k depends upon the data. In general, larger values of k will reduce the effect of noise on the classification, but cause boundaries between classes less distinct. In this paper, cross-validation is adopted to find out the best one for the classification. In k-fold cross-validation, the original sample is partitioned into k subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining $k-1$ subsamples are used as training data. The cross-validation process is then repeated k times, with each of the k subsamples used exactly once as the validation data. The k results from the folds then can be averaged to produce a single estimation.

Table 1 shows the result when adopting k-fold cross-validation to verify the correctness of our kNN classifier with the new features. As shown in Table 1, the system could produce better result when k equals to 3, so k's value could be determined as well.

3.6. Fall incident detection flow

The fall detection system in this paper will focus on indoor activities and Fig. 10 describes the fall incident detection flow and the intermediate events include standing posture event, lying posture event, and temporary posture event, while the final events include falling down event and lying down event. The kNN classifier could identify the intermediate events and the decision of a fall incident is determined by the event transition and time difference between events. In essence, it may lead to false alarms on fall incident event and lying down event, because these two events are similar. According to our experiments, the speed of transition is an important factor which can successfully distinguish these two events. In other words, if the transition time between temporary posture event and lying down event is less than certain threshold value, the probability of falling down event may be higher than lying down event.

Table 1
k-fold cross-validation result.

Testing : Training	k = 3 (%)	k = 5 (%)	k = 7 (%)	k = 10 (%)	k = 13 (%)	k = 15 (%)
1:9	96.67	95.33	94.00	93.33	92.67	92.67
1:4	94.67	94.00	94.00	93.33	93.33	93.33
1:1	94.67	95.33	95.33	93.33	90.67	90.67
Average	95.34	94.89	94.44	93.33	92.22	92.22

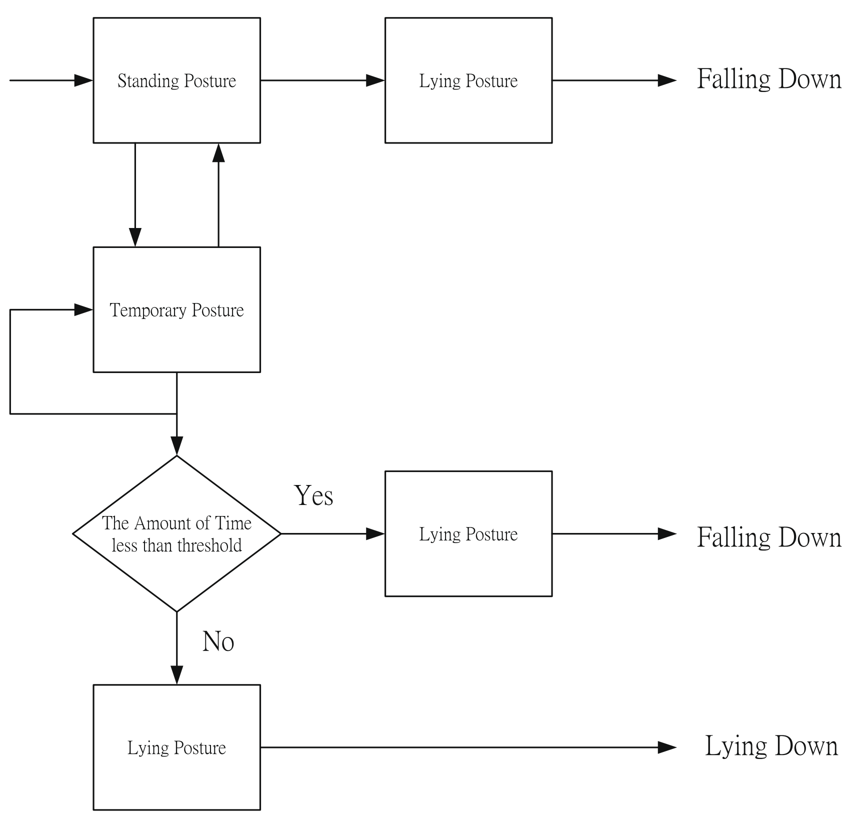


Fig. 10. Fall incident detection flow.

In order to obtain more objective threshold value, 30 fall incident cases are simulated and the transition time of the states are listed in Table 2. As shown in Table 2, the minimum transition time is 0.14 s, and the maximum is 0.34 s. Table 3 shows the statistical result of the simulation. Table 3 shows that the time difference is between 0.2262 s and 0.2658 s in 95% Confidence Interval (CI). In other words, the time difference average will fall on this interval with 95% probability. Therefore, it is reasonable to set the upper bound of threshold value as 0.3 s. As mentioned above, the surveillance equipment in the system is a cheap web camera and it could process five frames in one second. As a result, the upper bound of the threshold value is 0.4 s in this system.

It is necessary to verify the above result, and statistical analysis is used to verify the result. Two statistical analyses will be conducted in this paper: check sample data distribution and determine the threshold value. Hypothesis testing approach is adopted to verify the result, and the null hypothesis H_O and alternative hypothesis H_A are described as follows:

H_O: there is no difference between the distribution of the data set and a normal one
H_A: there is a difference between the distribution of the data set and a normal one

In sample data distribution analysis, Kolmogorov–Smirnov test is conducted and Table 4 is Kolmogorov–Smirnov test statements provided by SPSS. The P-value in Table 4 equals 0.749 which is larger than 0.05, so we could not reject H_O. Fig. 11 is a Quantile–Quantile plot which is constructed according to the simulation data in Table 2. Fig. 11 shows that the distribution of the data approaches to a straight-line, so this sample data can subject to normal distribution.

As described above, the assumption is that when fall incident happens, the average transition time of human body posture event will be less than 0.4 s and the transition time will subject to normal distribution. Statistical hypothesis testing is conducted to verify the critical value, and the null hypothesis H_O and alternative hypothesis H_A are described as follows:

H_O: Critical value $\mu = 0.4$
H_A: Critical value $\mu < 0.4$

T-test is used to verify the assumption, and Table 5 is the single sample T-test statistical statement and Table 6 is the result of sin-

Table 2
Fall incident simulation result.

ID	Temp state time	Lying state time	Difference
1	5.17	5.31	0.14
2	15.1	15.34	0.24
3	24.25	24.5	0.25
4	34.1	34.32	0.22
5	44.25	44.5	0.25
6	1.93	2.15	0.22
7	7.4	7.7	0.3
8	13.57	13.79	0.22
9	19.87	20.1	0.23
10	26.29	26.5	0.21
11	2.89	3.06	0.17
12	7.14	7.36	0.22
13	11.26	11.51	0.25
14	15.84	16.18	0.34
15	22.34	22.61	0.27
16	2.36	2.61	0.25
17	12.74	13.05	0.31
18	25.28	25.57	0.29
19	33.1	33.45	0.35
20	47.62	47.86	0.24
21	2.55	2.81	0.26
22	14.98	15.17	0.19
23	25.5	25.67	0.17
24	31.17	31.37	0.2
25	39.94	40.21	0.27
26	3.96	4.21	0.25
27	11.25	11.56	0.31
28	26.33	26.51	0.18
29	36.12	36.47	0.35
30	45.89	46.12	0.23

Table 3
Statistical information about fall incidents simulation.

		Result	Standard error mean
Difference	Mean	.2460	.00970
	95% CI of difference		
	Lower bound	.2262	
	Upper bound	.2658	
	5% Trimmed mean	.2456	

Table 4
Kolmogorov–Smirnov test.

		Difference
N		30
Normal parameters	Mean	.2460
	Std. deviation	.05315
Most extreme differences	Absolute	.137
	Positive	.137
	Negative	−.079
Kolmogorov–Smirnov Z		.749
Asymp. Sig. (two-tailed)		.630

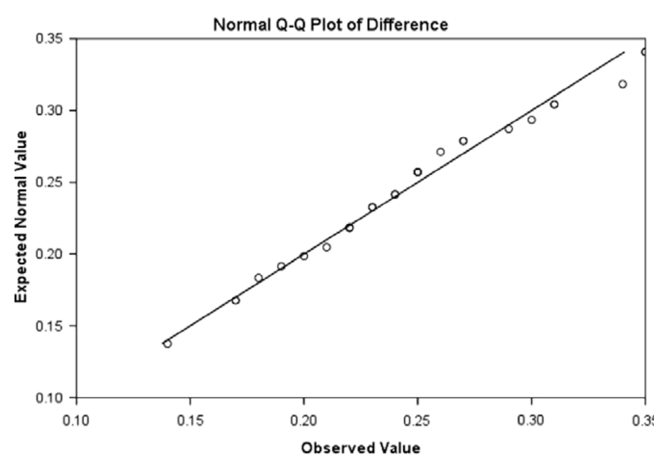


Fig. 11. Normal Q–Q plot of difference.

Table 5
One-sample statistics.

	N	Mean	Std. deviation	Std. error mean
Difference	30	.2460	.05315	.00970

Table 6
One-sample test.

	Test value = 0.4					
					95% CI	
	t	df	Sig. (two-tailed)	Mean diff.	Lower	Upper
Diff.	−15.870	29	.000	−.15400	−.1738	−.1342

gle sample *T*-test. As shown in Table 6, the *P*-value in 1-tailed is less than 0.05 and that means that H_O will be rejected at $\alpha = 0.05$ significance level. In other words, the alternative hypothesis H_A will be accepted and that means the average transition time from temporary posture state to lying posture state is less than 0.4 s when fall incident occurs. Thus, it is reasonable to use 0.4 s as the critical value to determine whether fall incident is taking place.

4. Experiments and results

Table 7 shows the equipment list in the experiment. The system will focus on how to increase accuracy rate of fall incident detection and discriminate fall incident and lying down events to reduce the number of false alarms.

4.1. Postures analysis

As described above, the human body postures are divided into standing posture, temporary posture, and lying posture, respectively. In the experimental environment, a fixed camera is used to monitor indoor activities when human body appears in the scene. Fig. 12 shows that the system detects standing, temporary, and lying postures. Meanwhile, Fig. 13 shows that the system could identify the posture even though the user stretches his hand in various way to affect the ratio of the human body height and width.

Table 7
Hardware list in the experiment.

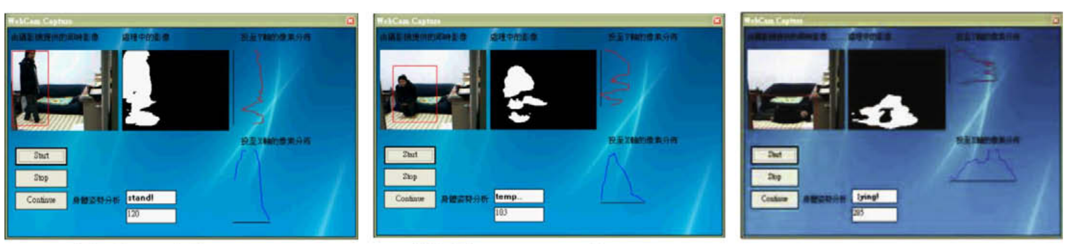
Web camera	Logic QuickCam STX
CPU	Intel(R) Core(TM)2 2.13 GHz
RAM	1.00 GB

4.2. Fall detection

In addition to the *k*NN classification model for posture classification, falling speed is used to determine whether a fall incident event occurs. Meanwhile, if the object's state transits from temporary posture state to lying down posture state in less than threshold value, the system will regard this transition as a fall incident. Fig. 14(a) and (b) shows the standing event and temporary event, respectively, while Fig. 14(c) shows the result of detecting fall incident event.

4.3. Result and discussion

In addition to the above experiments, 15 people including 10 males and 5 females are invited to join fall detection system experiment. Age of these people ranges from 24 to 60, weight ranges from 90 lb to 220 pounds and height ranges from 5 ft. to 6 ft. When



(a) Stand Posture (b) Temporary Posture (c) Lying Posture

Fig. 12. Three different postures identification.

(a) Upper Limb Activity 1 (b) Upper Limb Activity 2 (c) Upper Limb Activity 3

Fig. 13. Upper limb activities simulation.

(a) Standing Event (b) Temporary Event (c) Fall Incident Event

Fig. 14. Experiment result.

Table 8
Simulation result.

Fall accident system recognition	Yes	No
Positive	37	6
Negative	8	39

each person comes into the scene, he/she will try to simulate the lying down cases that they may encounter in daily life for three times and simulate fall incident cases that they may encounter for another three times. These simulations include different types of falls, and there are 45 lying down cases and 45 fall incident cases. Table 8 shows the result. The results in the experiment shows that the total accuracy rate is about 4.44%, the accuracy rate on lying down events is about 86.67%, and accuracy rate on fall incident detection is about 82.22%.

5. Conclusion

The main purpose of this paper is to use off-the-shelf devices to develop a fall detection system. In practice, video surveillance system may infringe privacy to those who use the system, so human body silhouette is adopted to improve privacy protection. Meanwhile, human body silhouette removed most of human body features, so height and width of human body silhouette are adopted as the features of fall incident detection in many studies. Practically, people may stretch out their hand to fetch something and that may affect the posture detection. In this paper, vertical projection histograms of the silhouette image and statistical method are performed on the projection to reduce the influence. In feature selection, the ratio of bounding box height and width and the difference of bounding box height and width are adopted as the system features in this paper. In fall incident detection, the system makes use of *k*NN to classify human body postures and the best *k* value in *k*NN algorithm is determined by *k*-fold cross-validation scheme. Meanwhile, a falling detection flow is adopted to detect fall incidents and the transition time from temporary posture state to lying down posture state is the critical factor used for fall incident detection. Statistical analysis is used to find out the transition time from the experiment data, and the value is verified by statistical hypothesis testing. The experiments show that it could reduce the effect of upper limb activities and the system has a correct rate of 84.44% on fall detection and lying down event detection.

Acknowledgment

This work was supported in part by the National Science Council under the Grants NSC-97-2221-E-009-135 and NSC-97-2811-E-009-019.

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