

A DYNAMIC MOTION PATTERN ANALYSIS APPROACH TO FALL DETECTION

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ABSTRACT

In this paper we present our work on human body movement analysis, especially on fall detection. We have developed a reliable dynamic motion pattern analysis algorithm to detect fall situation. The algorithm works on the digital signal output from waist-mounted accelerometry. It first filters noisy components with a Gaussian filter; secondly sets up a 3D body motion model which relates various body postures to the outputs of accelerometry; finally a dynamic detection process is applied to make decision. Experiments were done on 40 cases mimicking various body movements. Our approach gave right judgements in all cases. Our work is an important part of elder care and rehabilitation.

1. INTRODUCTION

Human fall can involve a violent one like tripping, or a weak one like fainting fall. Although the bumps and bruises caused by falls scarcely cause injury for young people, fall can injure the elderly in large scale. It has been found [1] that ten to fifteen percent falls will cause some serious physical injury in older people. The early detection of fall is an important step to alert and protect the subject, so that serious injury can be avoided. Fall detection is an important part of human body movement analysis. It is an area of increasing importance and interest to practitioners, researchers, and health industry.

Various automatic fall detection approaches have been proposed [2, 3, 4, 5, 6]. Among all the approaches, there are basically three generic ways including (a) video analysis-based, where real time movement of the subject is monitored through video channel; (b) acoustic frequency analysis-based, where falls are detected by analyzing the frequency components of vibration caused by the impact; (c) worn device-based, where falls are picked up by the devices attached to the subject. Although there are respective pros and cons among these approaches, the worn device-based approach is the most attractive method. This is because it is less expensive, more reliable, and can be easily embedded into existing community alarm and response systems.

In a belt-worn device-based fall detection system, a group of sensors are used. When movement happens, the signals from these sensors are analyzed. Based on the analysis, if the device detects a fall, alarm signal will be sent to service control centre to trigger corresponding reaction. There exist many belt-worn device-based fall detection systems [7, 8, 9], some are in commercial uses. Most of the systems used two kinds of sensors to detect fall. One is accelerometer which detects body motion in three planes, the other is tilt meter which determines the wearer's orientation. The performance of a belt-worn device-based fall detection system can be judged by several criteria, including degrees of complexity, user friendliness, false alarm rate, and correct alarm rate. Based on comprehensive study of the body kinematics and dynamics, we developed a simple yet reliable fall detection system using accelerometer.

In the rest of the paper, we describe details of our approach. The following section presents the algorithm in detail. Experiments and discussions on fall detection are described in section 3. Finally, conclusions will be made in section 4.

2. THE PRINCIPLES OF THE FALL DETECTION METHOD

A fall detector is a device that can detect various body falls and send out alarming signal to a remote end. This section discusses our accelerometer-based fall detection system.

2.1. The fall detection system

The system is composed of a belt-worn signal detecting block, a signal processing block, and a telecommunicating block. The belt-worn signal detecting block is composed of three dualaxial accelerometers (ADXL202E) which detect body acceleration in three planes (vertical, horizontal, and sagittal). Fall detecting algorithm is implemented in the signal processing block. In case of detecting a fall, alarm is sent out via the telecommunicating block. The rest of the paper is devoted to detailed discussion of the signal processing block.

The acceleration readings contain both the gravitational component and the inertial component caused by body motion. These two components are un-separable (only possible under some special conditions). Our fall detection algorithm works on the triaxial accelerometer reading, without considering a neat separation of the two components.

2.2. 3D body motion model – representing acceleration vector in 3D space

Based on basic theory of physics, especially the relationships among the gravity, acceleration, and motion, and based on the analysis of real output of accelerometer (the data reflected various activities including human standing, walking, sitting heavily, falling on the floor, and dummy model falling down), we represent the output of accelerometer as a vector \vec{A} in 3D space with axes X, Y and Z as in Fig. 1.

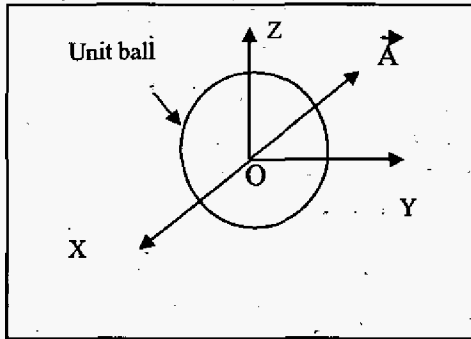


Fig. 1. An accelerometer output is represented as a vector \vec{A} in 3D space

The acceleration vector \vec{A} can be expressed as

$$\vec{A} = (A_x, A_y, A_z) = |A| \vec{U}_A \quad (\text{EQ 1})$$

where A_x, A_y, A_z are the projection of \vec{A} on X, Y and Z axes respectively, $|A|$ is the amplitude, and \vec{U}_A the unit vector.

With different body activity, the vector \vec{A} corresponds to a position in the space as detailed below.

- (1) still state: the subject may stand still, sit still, or lie still.

Here the vector is around the unit ball (its radius equals to g , which is the acceleration caused by gravity, with $g = 9.81 \text{ m/s}^2$), with a small amplitude variation represented with ΔA .

Still state can be classified as either normal or abnormal as:

- (1.a): normal still: when the subject is standing still, or sitting still.

Here the vector is around the unit ball near the Z axis. In this case, the angle of \vec{A} OZ (represented with ϕ) is less than a value Φ_T .

- (1.b): abnormal still: when the subject is lying still or upside down.

Here the vector is around the unit ball but away from the Z axis, with the angle of \vec{A} OZ larger than Φ_T .

- (2) active state: the subject may be walking, running, or jumping, etc.

Here the vector is away from the unit ball, could be either outside, or inside.

2.3. Dynamic fall detection

The digital signal output from the signal detecting block is first smoothed with Gaussian filtering to get rid of high frequency noise. Then the following fall detection through dynamic motion pattern analysis is used to detect fall event.

The fall detection algorithm consists of three stages.

Stage 1: fall onset detection

A possible fall is said to start if the following two conditions are met:

$$|\phi| < \Phi_T \quad (\text{EQ 2})$$

$$|A_x| > A_{x\text{fall}} \text{ , or } |A_y| > A_{y\text{fall}} \quad (\text{EQ 3})$$

By EQ 2, it assumes a fall can only start when the subject is in an upright position. This is a reasonable assumption and will reduce false alarm rate.

By EQ 3, it considers a big change will happen in either X or Y direction when a fall starts. Here $A_{x\text{fall}}$ and $A_{y\text{fall}}$ are thresholds decided by analysing real data.

Stage 2: fall confirmation detection

With a fall onset detected, after a time delay t_{slip} , fall confirmation detection is done to make sure the subject is in a fallen state. The state is confirmed when the acceleration amplitude is around g and the acceleration direction is away from the Z axis. This can be expressed as:

$$(1 - \Delta A) < |A| < (1 + \Delta A) \quad (\text{EQ 4})$$

$$|\phi| > \Phi_T \quad (\text{EQ } 5)$$

Stage 3: fall state detection

With a positive outcome of the stage 2, a fall state (expressed in EQ 4 and EQ 5) needs to be present for a period t_{down} for the system to formally send out a fall alarm signal.

3. EXPERIMENTS AND DISCUSSIONS

Fall detection experiments were done on four categories of data, namely, (1) human standing and/or walking, (2) human sitting heavily, (3) human falling on the floor, and (4) dummy model falling down.

For category 1, the subjects may either stand still, or walk around with various paces. In this category, 15 experiments were done with corresponding data recorded and analysed.

For all the 15 situations, the algorithm can recognize that no fall occurred and sent no alarm signal. Fig. 2 illustrates an example. For the case, the algorithm made a right judgement, i.e., no fall happened.

For category 2, the subject tried to sit heavily to cause a false fall situation, but the subject kept sitting upright. In this category, 7 experiments were done with corresponding data recorded and analysed.

For all the 7 situations, the algorithm can recognize that although fall onset were detected at early stage, but following analysis in stage 2 and stage 3 will realise that the fall had recovered and no need to send alarm signal. Fig. 3 illustrates such an example.

For category 3, the subject fell down to the floor naturally. To mimic the real situation, we designed two sub-experiments in this category. In one sub-experiment, after falling down, the subject returned to upright position quickly. In the other sub-experiment, after falling down, the subject kept in lying posture. In this category, 10 experiments were done with corresponding data recorded and analysed.

For all the 10 situations, the algorithm could first detect a fall onset, then verify if the state is lasting, finally make decision on whether to send alarm or not. Fig. 4 and 5 illustrate two examples. In Fig. 4, though a fall was detected at the 1611th sample, the algorithm figured out that the subject returned to upright position at the 4111th sample. Therefore no fall alarm will be sent out. This kind of judgement is exactly what a practical fall alarming system will pursue. A fall alarm will be sent out for Fig. 5 case. This is reasonable, since the subject kept lying for a period (more than 2.5 seconds) after falling down at about the 1280th sample. An emergent treatment will be necessary for the case.

For category 4, the design of the experiment is the same as category 3, but a dummy model was used instead of a person. In this category, 8 experiments were done with corresponding data recorded and analysed.

For all the 8 situations, the algorithm correctly picked up all the two situations. In situation one, the model fell down and kept down. In the other, the model fell down but quickly recovered to upright position.

A further experiment was designed to test the performance of the algorithm on dealing with the situation where the subject intentionally lay down slowly. In that case, the system did not consider it as a fall case.

4. CONCLUSIONS

This paper describes a reliable dynamic motion pattern analysis algorithm to detect fall situation. The novelty of the approach is that a three stage dynamic process is used to achieve right fall detection. Four categories of motion were designed to evaluate the algorithm. For all the four categories, a very reliable decision can be made on fall judgement. In our experiments, no false fall alarm occurred.

Fall detection using accelerometers is a part of human body motion analysis. Further work on human body motion analysis could involve more complicated gait analysis such as walk pattern separation, fall prediction which will lead to fall prevention, etc.

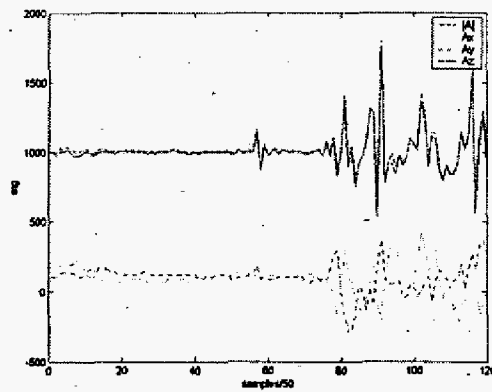


Fig. 2. When subject walked, the algorithm detected no fall.

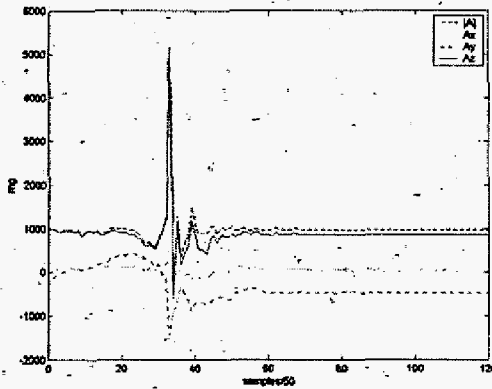


Fig. 3. When the subject sat heavily and kept upright posture, no fall alarm was sent.

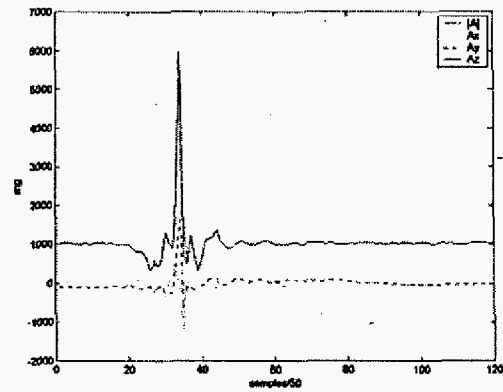


Fig. 4. When the subject fell (at about the 1611th sample) but returned to upright position quickly, no fall alarm was sent.

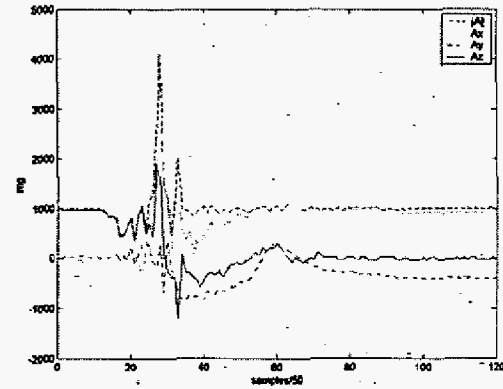


Fig. 5. When the subject fell (at about the 1280th sample) and kept lying down, a fall alarm will be sent out. An emergent procedure will be followed.

5. REFERENCES

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