

**NANYANG
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Fall detection based on 3D joint trajectory

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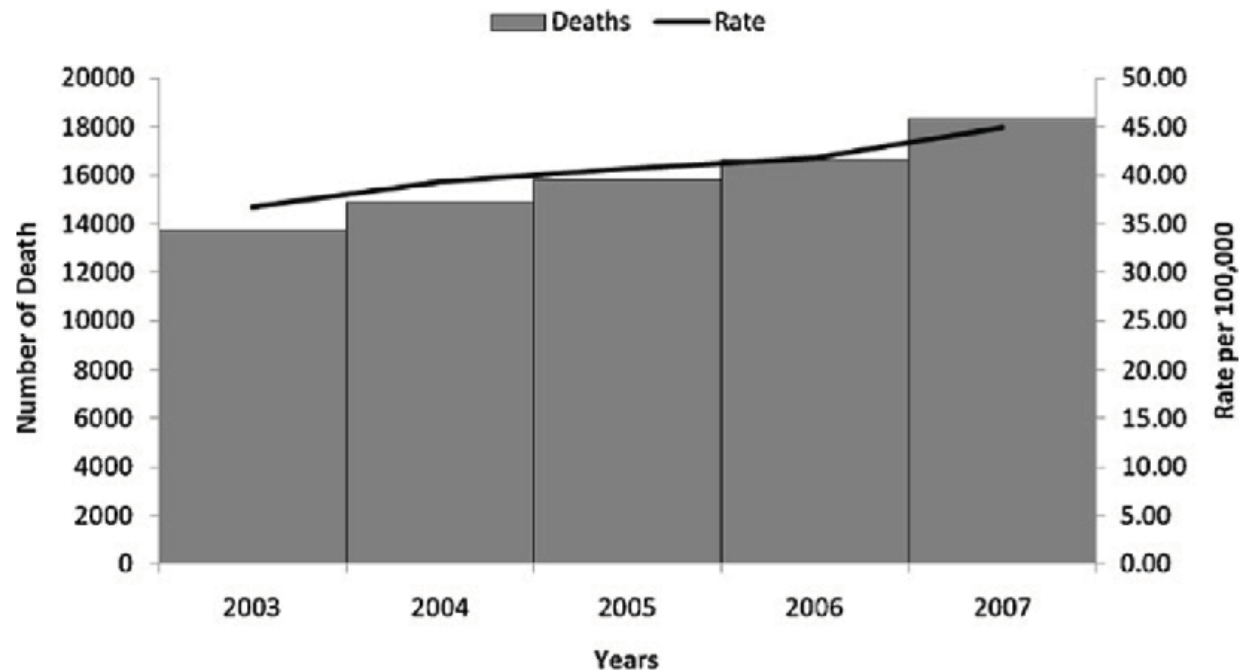
Outline

- Motivation
- Related works
- Proposed approach
- Results

Motivation

- The medical definition of a fall is:
An event which results in a person coming to rest unintentionally at a lower level [1]
- One of the biggest risks for elderly people is fall accidents, especially for the elderly people living alone.
- Getting help quickly after a fall reduces the risk of death by over 80 % and the risk of hospitalization by 26 %[2].

Motivation



The death rate by fall is increased with the years. During 2003-2007, the average rate was 41 per 100,000 population (about 80,000 falls fatalities) reported among the U.S. elderly people; it rose from 13,800 to 18,000 between 2003 and 2007 [3].

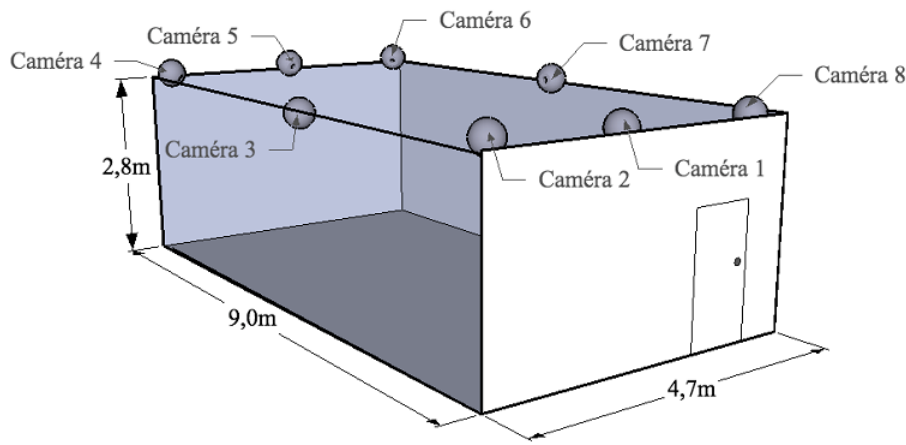
Motivation

One of the main reasons for low acceptance of the available technology for automatic fall detection is that the existing algorithms generate too many false alarms.

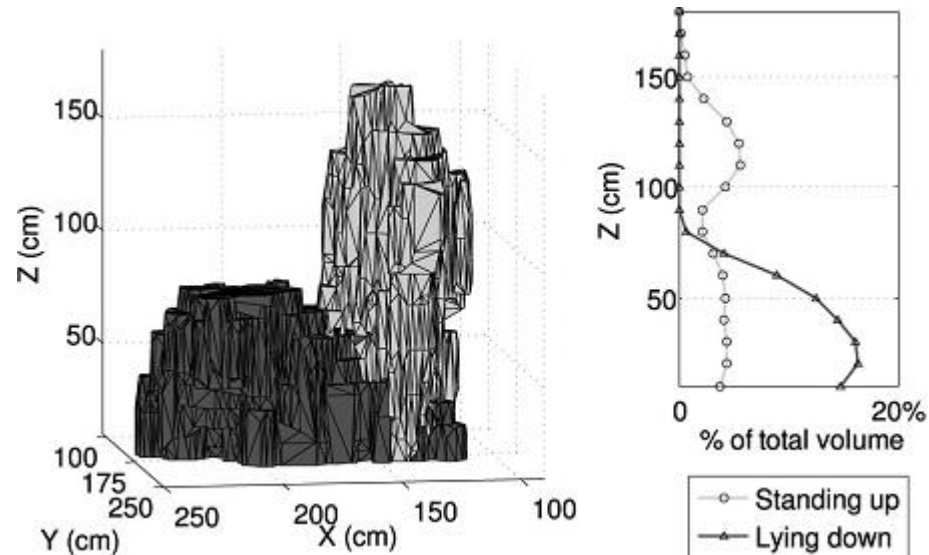
Related works

- Fall detection methods :
 1. non-vision based method
 2. vision based method
- Vision-based methods are non-intrusive methods, and they can detect the useful environment information around the object.
- The fall motion is very fast, and it just takes few hundreds milliseconds. Most vision-based existing methods cannot capture the specific motion during the fall phase.
- The feature of the vision-based systems can be posture, shape in-activity/change, 3-D silhouette vertical distribution, 3D silhouette centre and 3D orientation of the body.

3D silhouette vertical distribution[4]

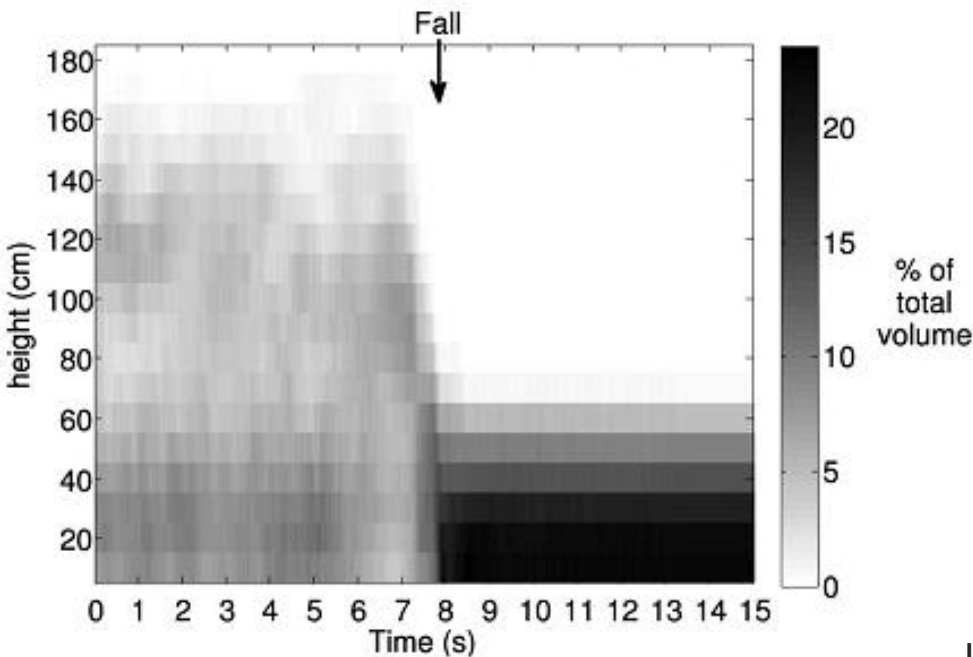


Camera configuration

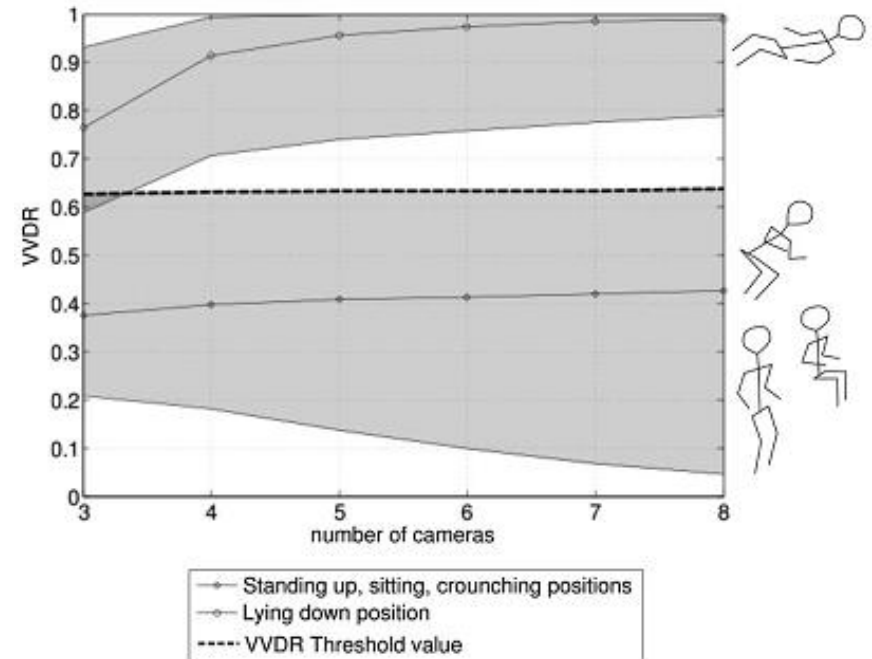


3-D reconstruction of a person after fusion of the different points of view and their corresponding vertical volume distribution (VVD) on the right.

3D silhouette vertical distribution[4]



Example of the VVD during a fall scenario



Influence of the number of cameras on the capability of the VVD-Ratio to discriminate body postures obtained without artificial occlusions. The grey areas correspond to 95% confidence intervals and the solid lines are the medians

3D silhouette vertical distribution[4]

INFLUENCE ON THE IMPLEMENTATION ON
COMPUTATION TIME

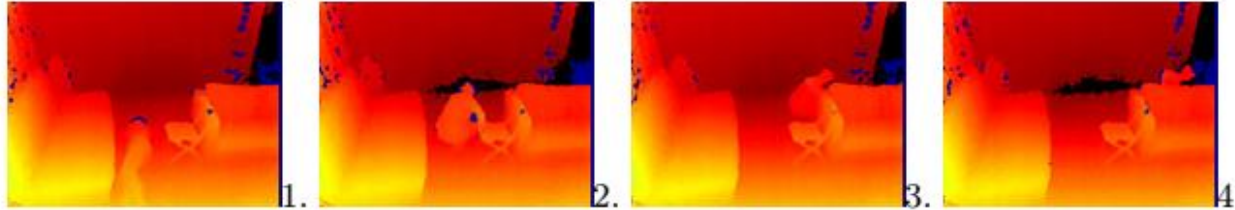
Segmentation	CPU	CPU	GPU
Projection	CPU	GPU	GPU
Number of cameras	time (msec/frame)	time (msec/frame)	time (msec/frame)
3	1140	98	63
4	1516	100	72
5	1888	111	79
6	2258	122	88
7	2613	133	96
8	2980	145	105

3D silhouette centre [5]

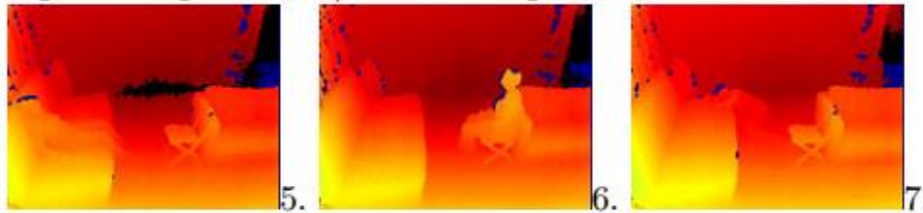
- This approach is based on depth camera.
- Silhouette---the foreground pixels
- If the body distance (silhouette centroid) from the ground distance lower than a threshold, then a fall is directly detected.
- The distance from the 3D centroid to the ground plane can directly be obtained by a simple point-plane distance:

$$D = \frac{|aX_c + bY_c + cZ_c + d|}{\sqrt{a^2 + b^2 + c^2}}$$

3D silhouette centre [5]

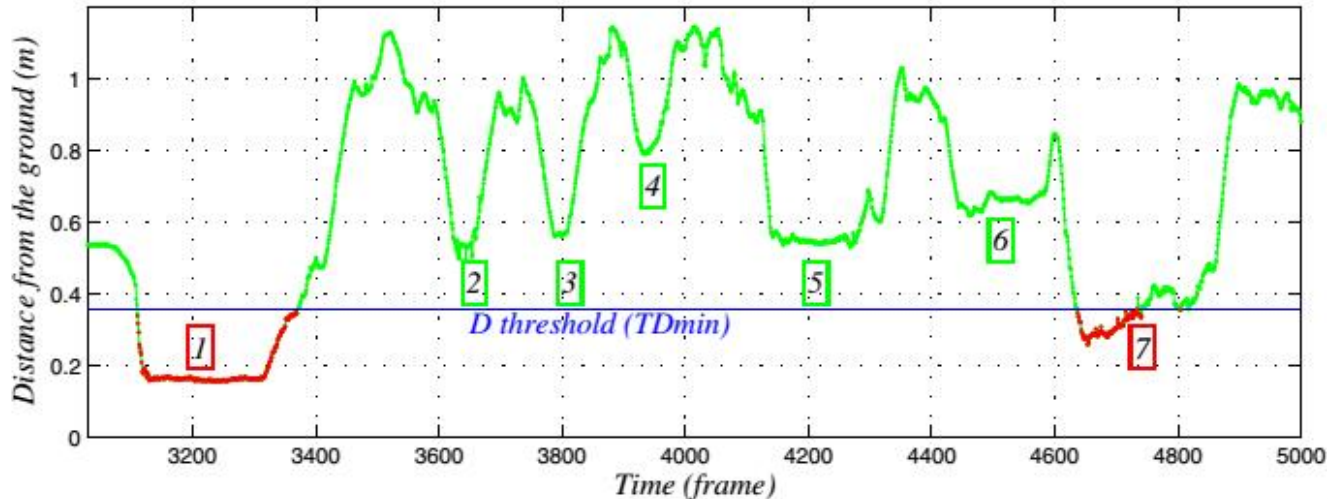


1. fall ending on the ground, 2./3. crouching down, 4. occluded crouching down



5. sitting down in the sofa, 6. sitting down on a chair, 7. fall ending on the sofa

numbered depth images



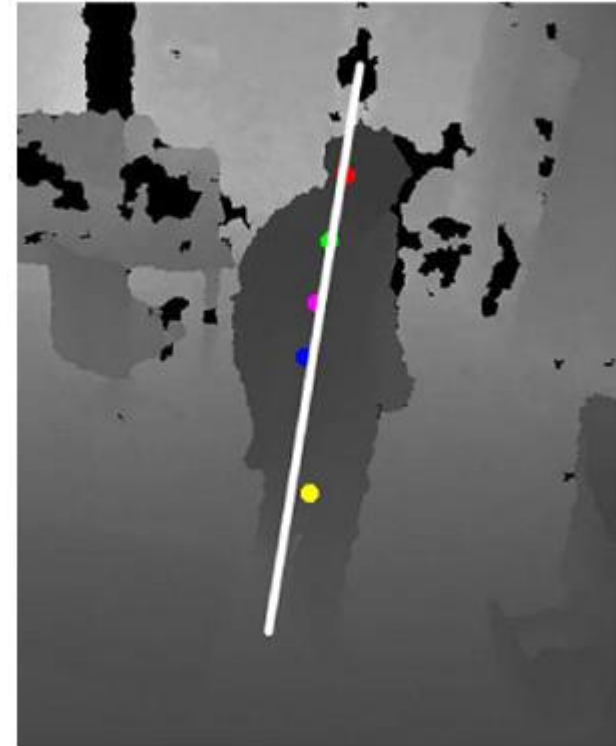
Distance-from-the-ground curve

3D silhouette centre [5]

- This algorithm cannot distinguish the fall accident and the non-impact initiative activities well since it does not consider the motion together.
- The centre location is easily distorted by moving object and bad segmentation.
- The simple threshold is a empirical value.
- It is prone to generate many false alarms.

3D orientation of the body[6]

- If the orientation of body is parallel to the floor and the spine distance to the floor is smaller than a threshold, a fall is detected.
- The orientation of the major axis is calculated using the coordinates of the head, shoulder, spine, hip and knee joints.
- Each joint is based on the skeleton extracted from Kinect SDK

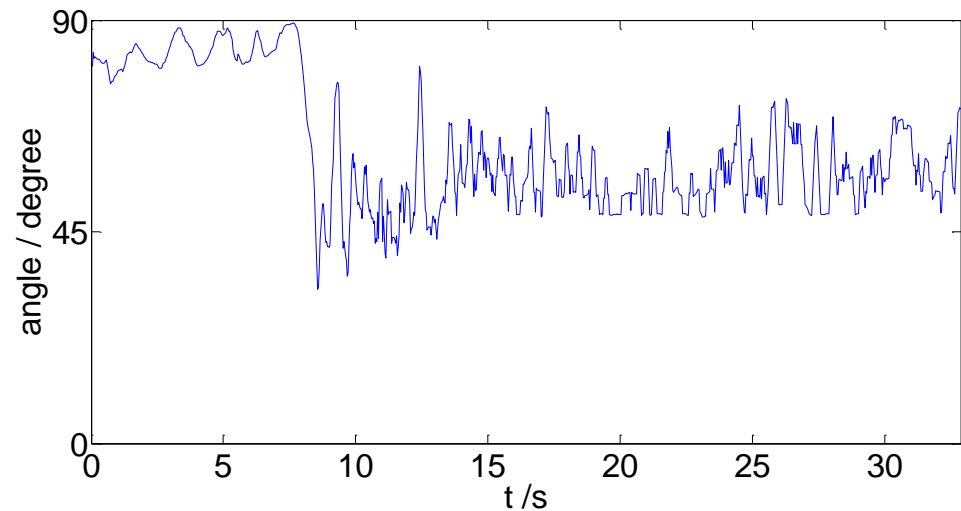


3D orientation of the body[6]

- However, the orientation based on the Kinect SDK is not robust when the person is not in upright position.

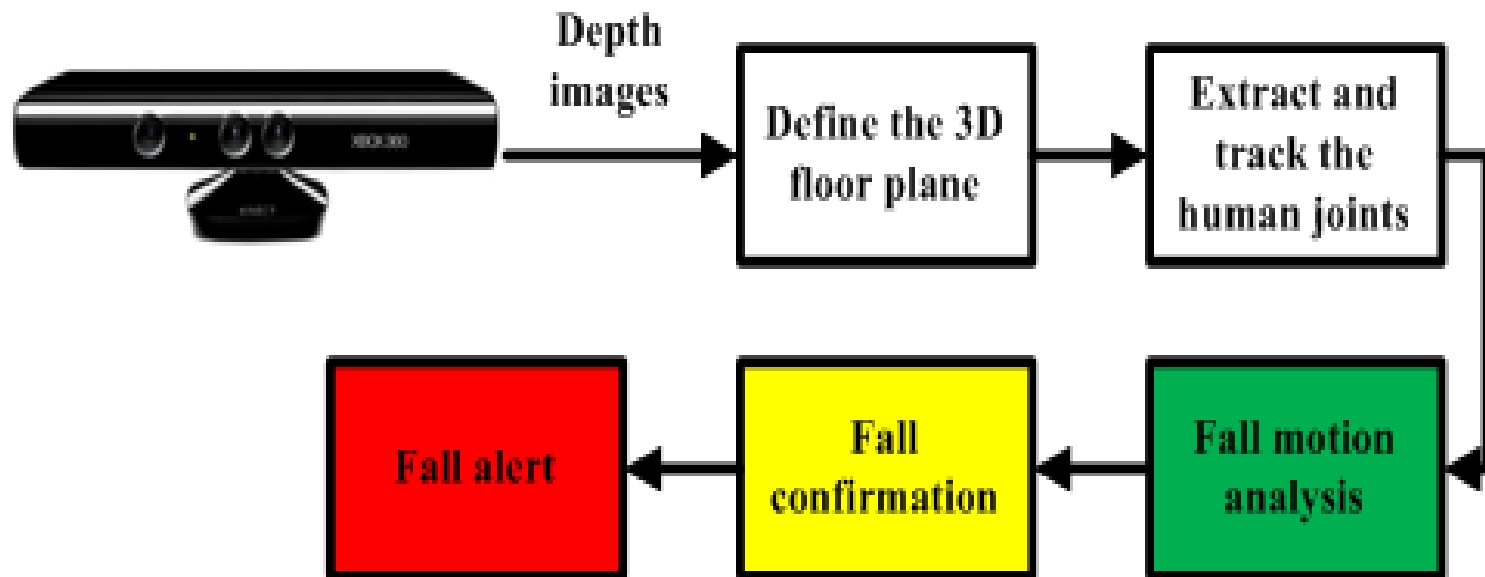


The subject lying on the floor

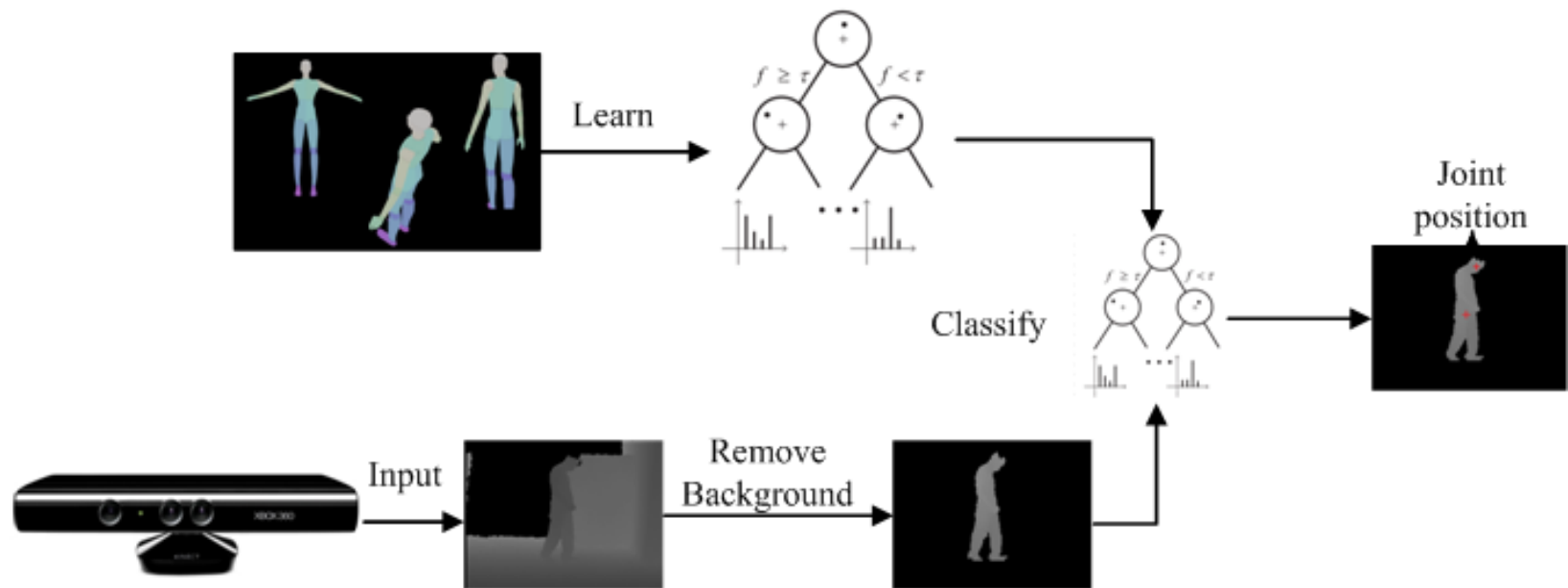


The angle between the 'orientation' and floor

Proposed approach

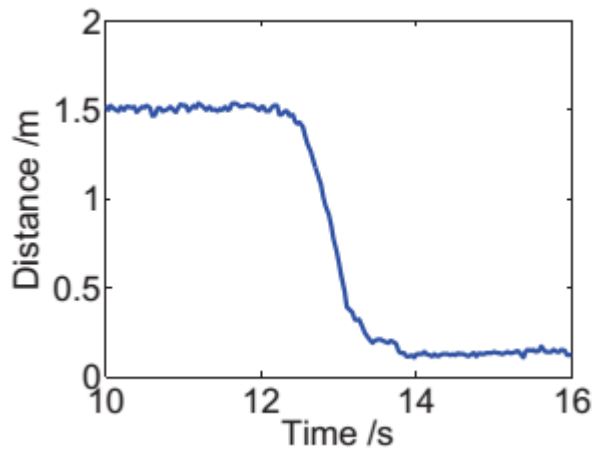


Proposed approach

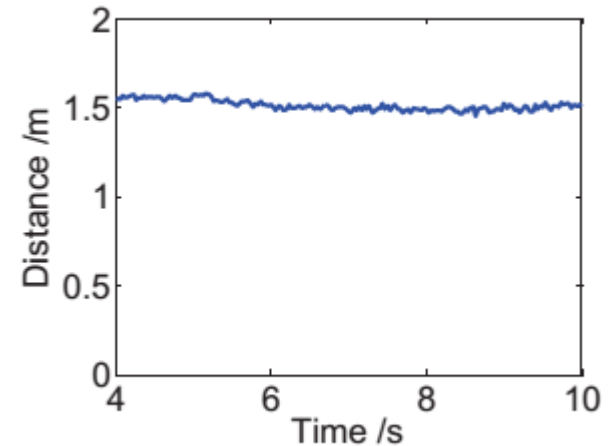


Proposed approach

The fall motion can be classified by support vector machine (SVM) based on the head trajectory



fall pattern



non-fall pattern (walking)

Two patterns of head distance trajectory from a video sequence

Results

Performance evaluation metric

(1) True positives (TP): the number of fall events detected correctly.

(2) True negatives (TN): the number of non-fall events detected correctly.

(3) False positives (FP): the number of non-fall events detected as fall events.

(4) False negatives (FN): the number of fall events detected as non-fall events.

(5) Sensitivity (Se): the capacity to detect fall events $Se = \frac{TP}{TP + FN}$

(6) Specificity (Sp): the capacity to detect non-fall events $Sp = \frac{TN}{TN + FP}$

(7) Accuracy (Ac): the correct classification rate

$$Ac = \frac{TP + TN}{TP + TN + FP + FN}$$

(8) Error rate (Er): the incorrect classification rate

$$Er = \frac{FP + FN}{TP + TN + FP + FN}$$

Results

	[5]	[6]	Proposed
TP	50	47	48
TN	25	32	50
FP	25	18	0
FN	0	3	2
Se(%)	100	94	96
Sp(%)	50	64	100
Ac(%)	75	79	98
Er(%)	25	21	2



Publications

- [1] Z.P. Bian, L.P. Chau, and N. Magnenat-Thalmann, “A depth video approach for fall detection based on human joints height and falling velocity,” in International Conference on Computer Animation and Social Agents, May 2012.
- [2] Z.P. Bian, L.P. Chau, and N. Magnenat-Thalmann, “Fall detection based on skeleton extraction,” in Proceedings of the 11th ACM SIGGRAPH International Conference on Virtual-Reality Continuum and its Applications in Industry. New York, NY, USA: ACM, 2012, pp. 91–94.
- [3] Z.P. Bian, J. Hou, L.P. Chau, and N. Magnenat-Thalmann, “Fall Detection Based on Body Part Tracking Using a Depth Camera,” IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, major revision.

References

- [1] W. H. O., “WHO global report on falls prevention in older age,” World Health Organization (WHO) Library Cataloguing-in-Publication Data, 2007.
- [2] Noury N, Rumeau P, Bourke A, O’Laighin G, Lundy J (2008) A proposal for the classification and evaluation of fall detectors. Biomed Eng Res (IRBM) 29(6):340–349
- [3] H. Alamgir, S. Muazzam, and M. Nasrullah. Unintentional falls mortality among elderly in the united states: Time for action. Injury, 43(12):2065 -2071, 2012.
- [4] E. Auvinet, F. Multon, A. Saint-Arnaud, J. Rousseau, and J. Meunier, “Fall detection with multiple cameras: An occlusion-resistant method based on 3-d silhouette vertical distribution,” IEEE Transactions on Information Technology in Biomedicine, vol. 15, no. 2, pp. 290–300, 2011.
- [5] C. Rougier, E. Auvinet, J. Rousseau, M. Mignotte, and J. Meunier, “Fall detection from depth map video sequences,” in Proceedings of the 9th international conference on Toward useful services for elderly and people with disabilities: smart homes and health telematics. Berlin, Heidelberg: Springer-Verlag, 2011, pp. 121–128.
- [6] C. Rougier, E. Auvinet, J. Rousseau, M. Mignotte, and J. Meunier, “Fall detection from depth map video sequences,” in Proceedings of the 9th international conference on Toward useful services for elderly and people with disabilities: smart homes and health telematics. Berlin, Heidelberg: Springer-Verlag, 2011, pp. 121–128.

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