Detection and Classification Method for a Temporary Change in Walking

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A short resume of the presenter

- Shin Morishima is an assistant professor in the Faculty of Engineering at Toyama Prefectural University.
- His research interests include human activity recognition, GPU-based system, machine learning.
- He received a PhD in engineering from Keio University in 2018.

Two ways for reducing fall damages

- Aging population increase damage of falls
  - Older people are more likely to be seriously injured by falls
  - In the USA, the cost for fall-related injury was approximately $50 billion in 2015

Two approach for reducing fall damages

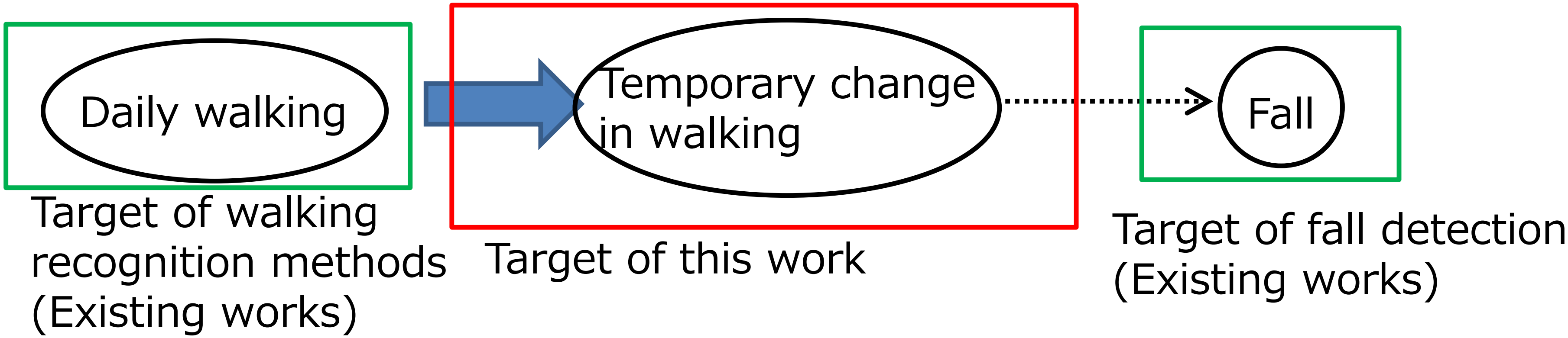
- Fall detection
  - It prevents fall-related injuries becoming severe

Existing work

Target of this work

- Detection of actions causing falls
  - It can help reduce the incident causing falls

Two ways for reducing fall damages

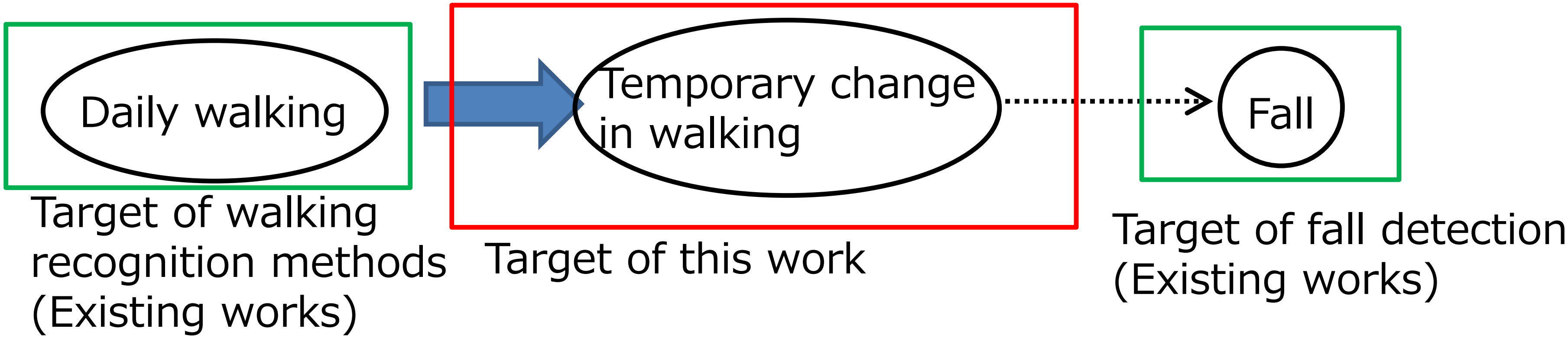


- A temporary change in walking occurs prior to a fall
  - Examples that could cause a fall; stumble stagger
  - Including actions that are not problematic: e.g. standstill

- Detection and classification method for temporary change in walking

Our proposal

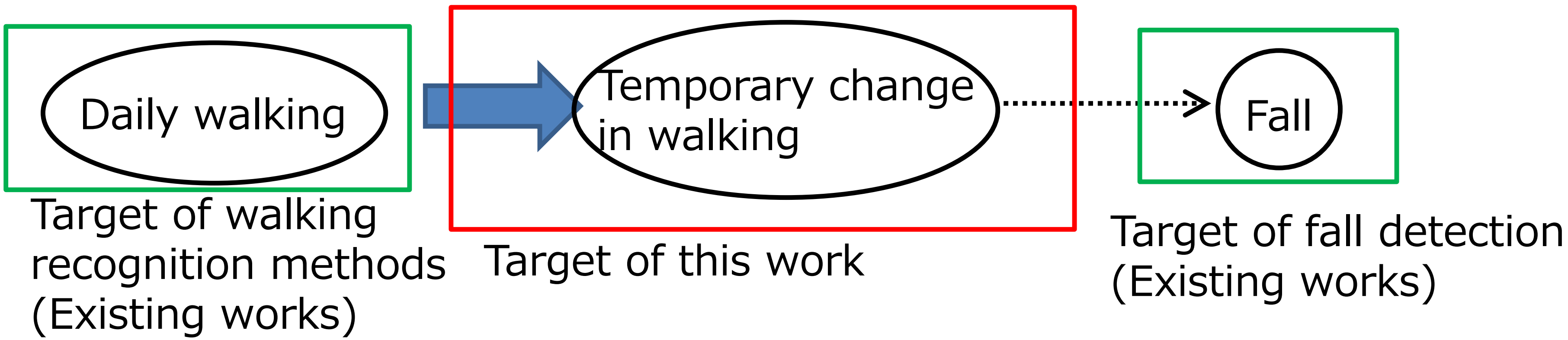
Existing work: walking recognition



- Walking recognition can distinguish walking and other activity
  - [1] classified walking and other 11 activities (e.g., running and skipping) from the data of video-based four joint coordinates
- The methods and our method can be used together to detect walking in several activities using the methods and to recognize a change in walking using our method

[1] J. W. Davis and S. R. Taylor, "Analysis and recognition of walking movements," in Proc. of International Conference on Pattern Recognition, Aug. 2002, pp. 315–318.

Existing work: Fall detection [2]

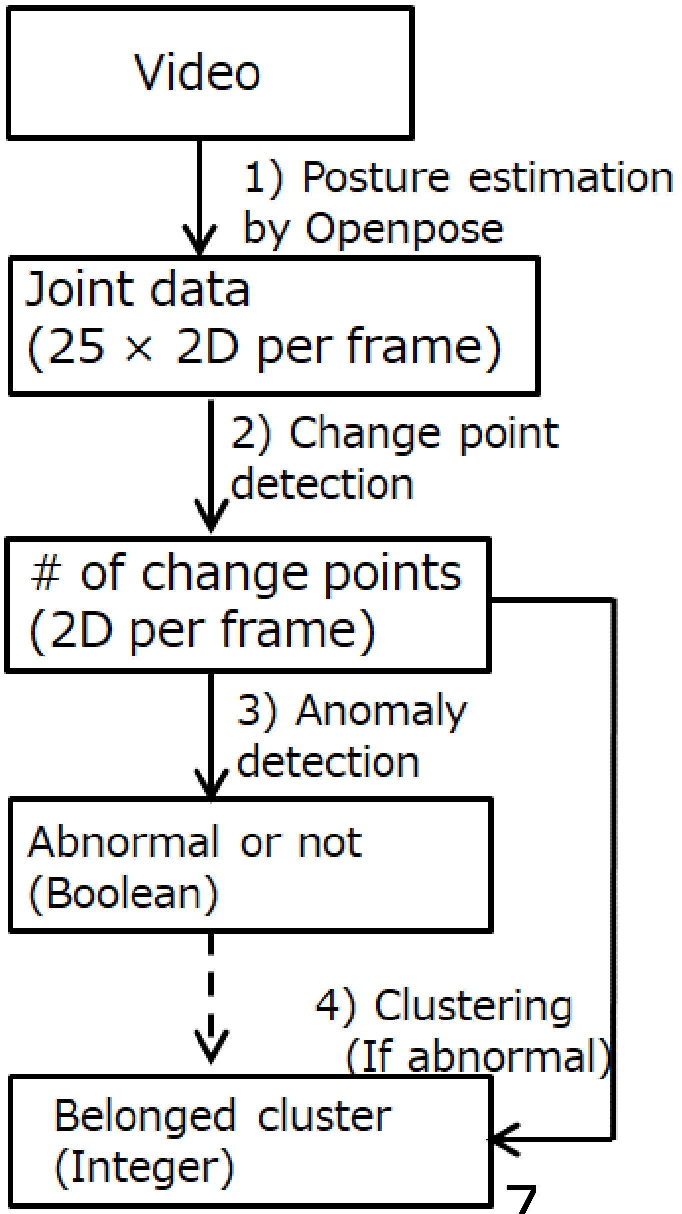


- Fall detection detects a fall after or just before it occurs
  - Reduce damage in the event of a fall
  - It cannot reduce the number of falls itself
- It also can be used together
  - Out method help reducing the falls itself

[2] L. Ren and Y. Peng, "Research of fall detection and fall prevention technologies: A systematic review," IEEE Access, vol. 7, 2019, pp. 77702–77722

Overview of proposed method

- The method use human joint data
  - In this work, it obtained by video using Openpose [3]
- Detection is performed by two steps
  - Change point detection and anomaly detection
- Classification is performed by clustering for the result of the anomaly detection



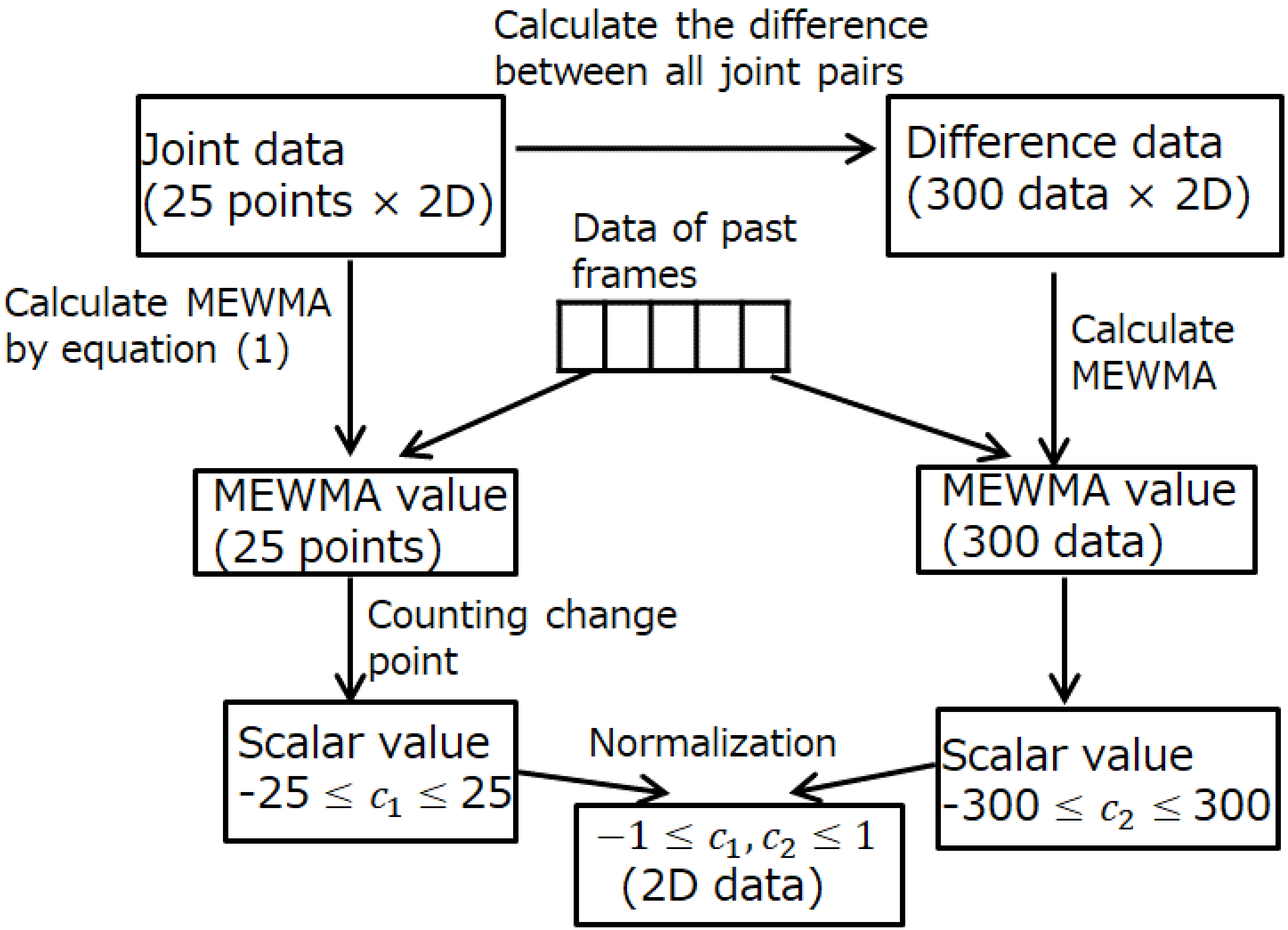
[3] Z. Cao, T. Simon, S. Wei, and Y. Sheikh, "Realtime Multi-Person 2D Pose Estimation using Part Affinity Fields," in Proc. of the 2017 IEEE Conference on Computer Vision and Pattern Recognition, Jul. 2017, pp. 1302–1310.

Step 1:Change point detection

- Change point detection is performed for time series of each joint and difference data
  - Difference data means difference between all pairs of joints (so, 300 difference data per frame)
- Each change point is performed by MEWMA [4]
  - Mahalanobis distance based method
  - Judging whether each joint or difference of each frame is change point
- The number of change point of each frame is used for anomaly detection (next step).

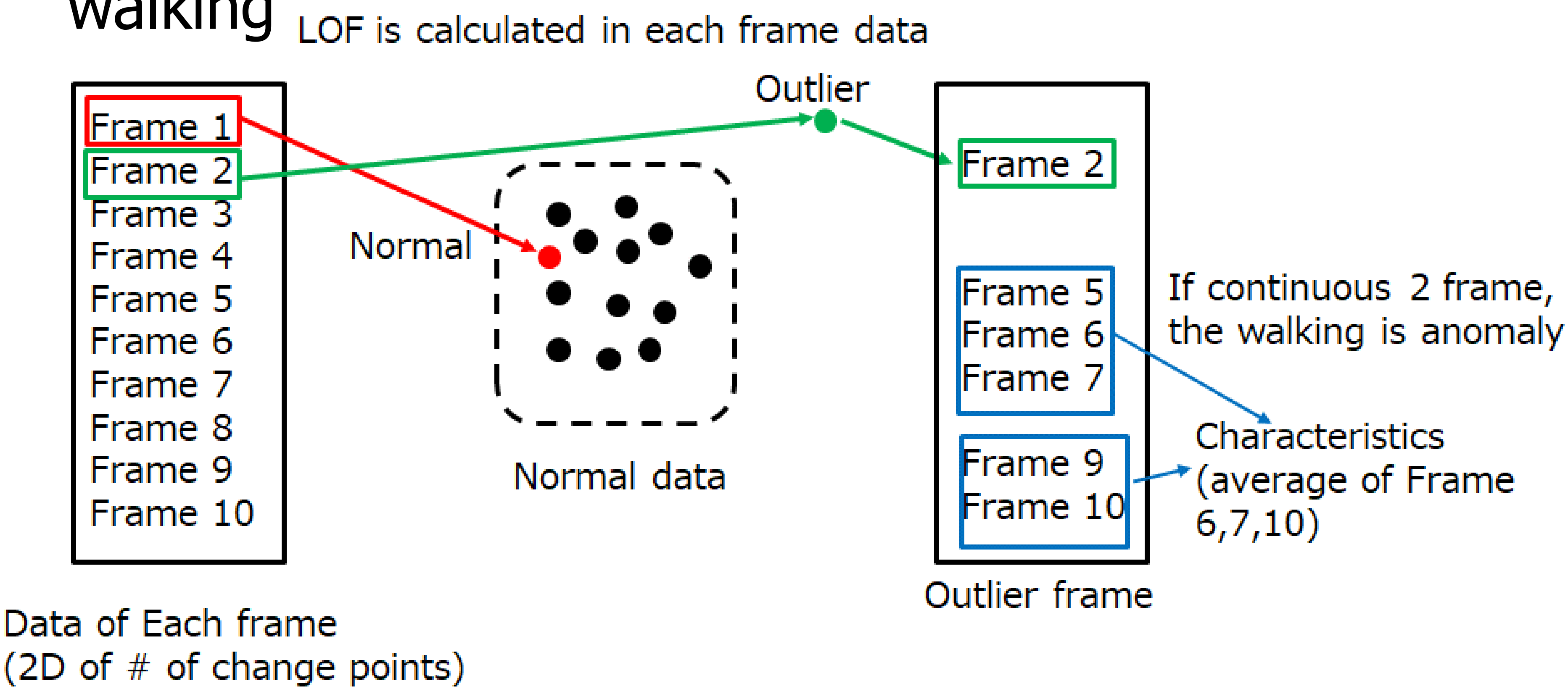
[4] C. A. Lowry, W. H. Woodall, C. W. Champ, and S. E. Rigdon, "A Multivariate Exponentially Weighted Moving Average Control Chart," Technometrics, vol. 34, Feb. 1992, pp. 46–53.

Flow of change point detection



Step 2: Anomaly detection

- Walking is detected anomaly when continuous two frame is judged as anomaly by LOF [5]
- The average of anomaly is characteristics of the walking



[5] M. M. Breunig, H.-P. Kriegel, R. T. Ng, and J. Sander, "Lof: Identifying density-based local outliers," in Proc. of the 2000 ACM SIGMOD International Conference on Management of Data, May. 2000, pp. 93–104.

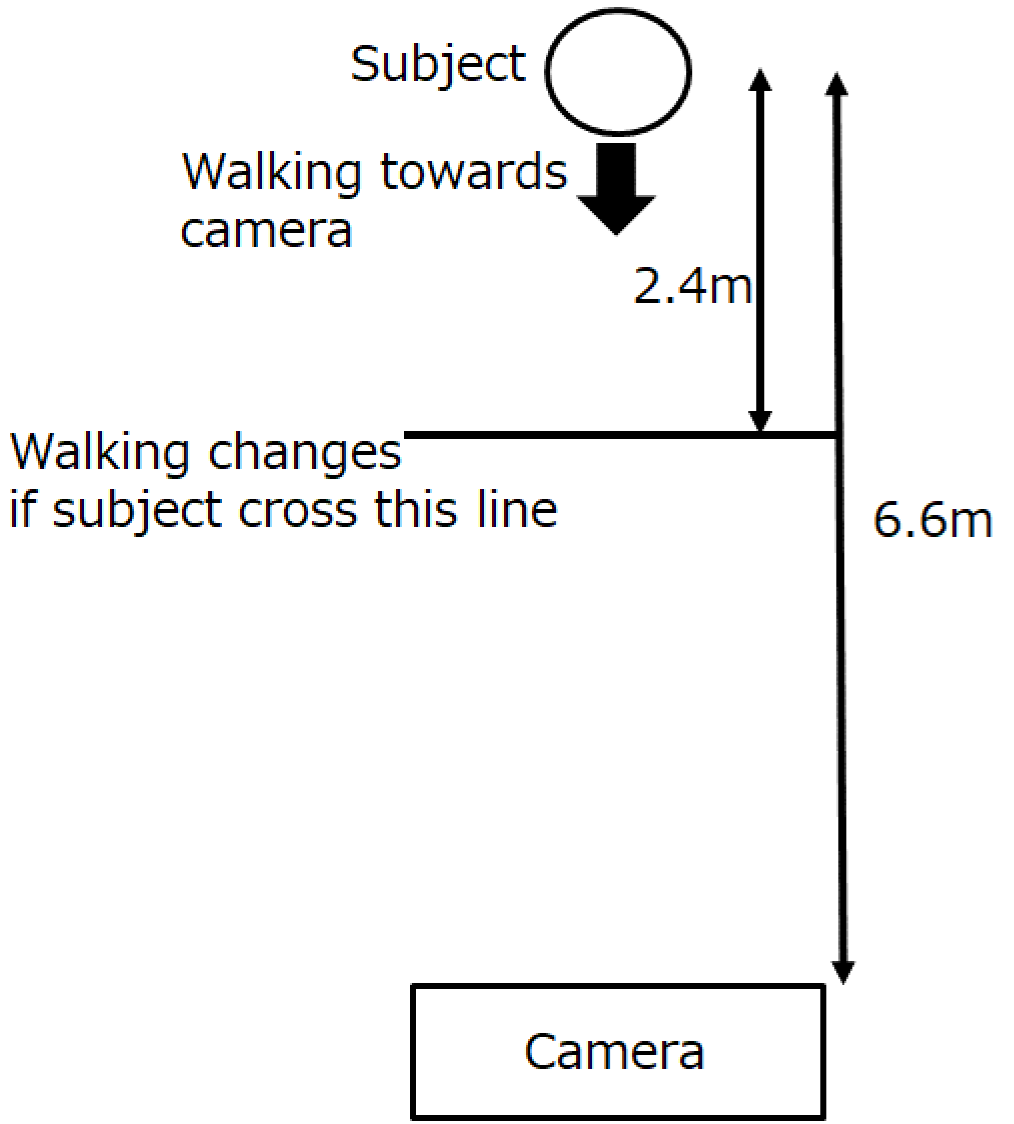
Step 3: Clustering

- Anomaly walking is classified
- The 2D characteristics is calculated by Step 2
- K-means is performed using the characteristics
  - 1) The center of gravity of each cluster is calculated.
  - 2) Each point is reclassified into the cluster which has the nearest center of gravity from the point.

Evaluation environment

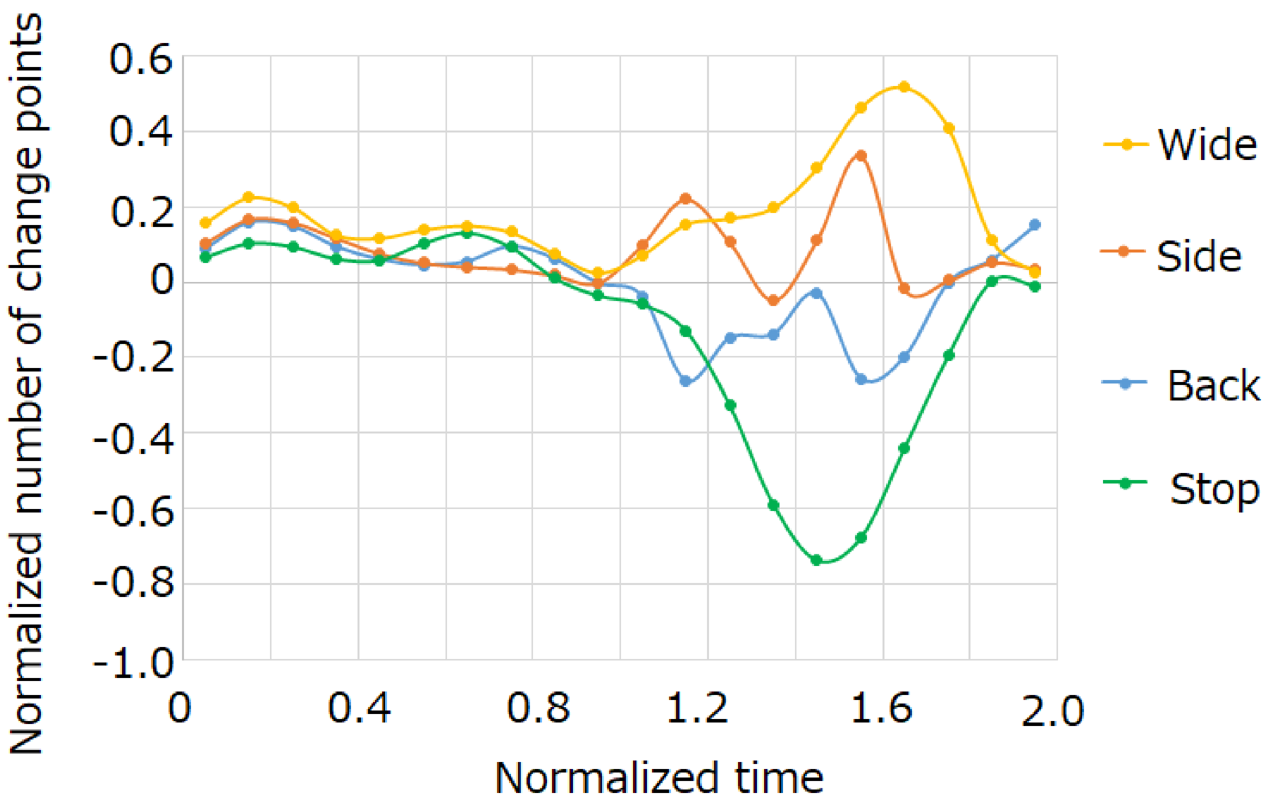
- Shooting walking video
  - 30fps, resolution:1,920 × 1,020
- Three adults
- Normal walking and Four types temporary change of walking
  - Back: Go back one step and start walking again
  - Side: Walk 40 cm from side to side
  - Stop: Stop and start walking again
  - Wide: Walk one large step (1 m)
- 20 data of each walking type

Evaluation environment



Result of change point detection

- Transition of the number of change point
- The case of joint data
- 0-1:daily walk, 1-2: anomalous walk (normalized time)



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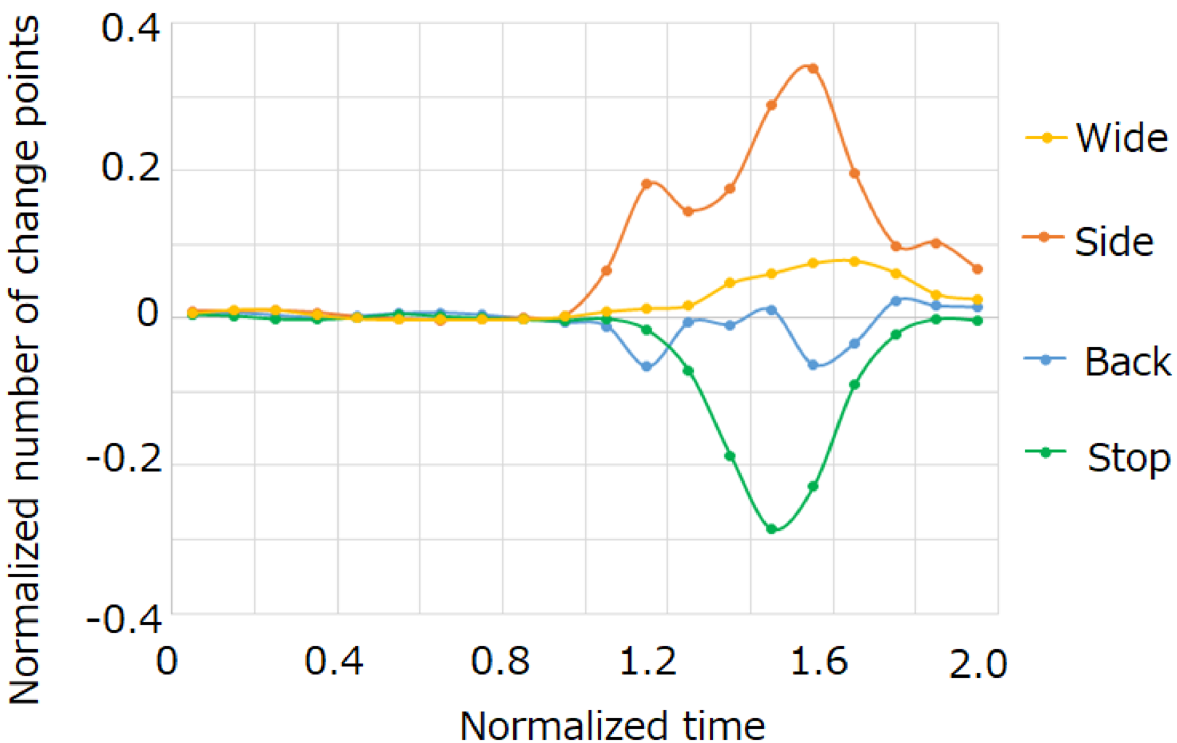

Result of anomaly detection

- True positive (TP) and false positive (FP) of each walking
  - FP means walking before changing is detected as anomaly
  - The number of data of each type and subject is 20
- TP rate is 91.7% and FP rate is 12.9%

Walking type	Subject A		Subject B		Subject C		Total	
	TP	FP	TP	FP	TP	FP	TP	FP
Back	14	0	20	6	20	4	54	10
Side	18	0	20	2	20	2	58	4
Stop	20	2	20	1	20	2	60	5
Wide	17	4	18	6	13	2	48	12
Total	69	6	78	15	73	10	220	31

Result of classification

- The detected anomalies are classified
- Four types of detected anomaly walking into three clusters in 89.1% on the basis of each characteristic
  - Each cluster seems like Back and Stop, Side, and Wide

Walking type	Cluster 1	2	3
Back	46	0	8
Side	0	54	4
Stop	58	0	2
Wide	0	10	38

Summary

- Detection and classification of temporary change of walking can help reduce incident causing falls
- We propose three steps methods
  - Change point detection
  - Anomaly detection
  - Clustering
- The method can detect the change in 91.2%
  - In four types of the changes
- Clustering can classify 89.1% of detected walking