Fall Risk Detection for the Elderly using Contactless Sensors

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Abstract

In recent years, Japan's elderly population has been growing. As a method of reducing the nursing care period, we studied a fall risk detection for elderly people. Our aim is to detect the fall risk with contactless sensors. First, we took a video of the 5-meter walking test by 36 subjects. Then, we processed them using OpenPose. Finally, rehabilitation exercise instructors evaluated the fall risk at 2 levels. In this paper, we reported on 3 machine learning models and evaluated the accuracy of the fall prediction. As a result, we found that sufficient accuracy can be obtained even with contactless sensors.

Introduction

In recent years, Japan's elderly population has been growing. The proportion of elderly people is estimated to reach about 30% in 2025 and about 40% in 2060. In the future, there will no longer be enough young people to take care of the elderly. Therefore, it is necessary to keep people healthier for longer and reduce the nursing care period. Injuries among the elderly are often caused by fractures due to falls.

Contact sensors or contactless sensors are used for a fall risk detection. There is a related study on fall risk detection using many contact sensors (Gervásio et al. 2016). However, contact sensors should not be used for elderly people with dementia because of a risk of the accidental ingestion.

Our aim is to detect the fall risk with contactless sensors. OpenPose is an open-source platform that can output 24 parts as two-dimensional coordinates on single images (Cao et al. 2017). Therefore, we can obtain walking information without contact using OpenPose. There are studies that utilized OpenPose for the detection of falls and diagnosis of gait disturbance (Solbach et al. 2017; Esmaeilzadeh et al. 2018). However, they do not evaluate the fall risk. In this paper, we evaluated the fall risk detection for Elderly using OpenPose.

Fall Risk Detection

Video Camera Settings

We took a video of 36 people taking a 5-meter walk test using a video camera (SONY: HDR-CX470W) on a flat place without obstacles. A space of 3-meters at the start and end of walking was set as the preparation section and the remaining walking section of 5-meters was evaluated (Figure 1).

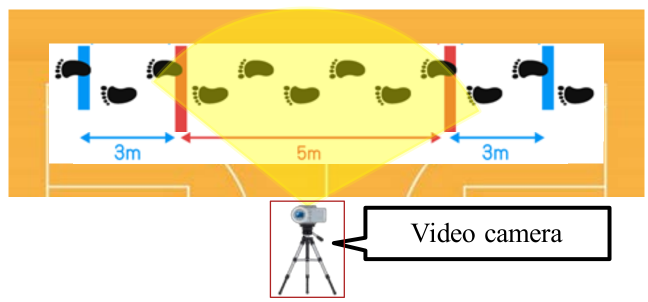


Figure 1: Video capture method for the 5-meter walk test.

Extracted Features

The photographic data was then processed using OpenPose. From the rehabilitation exercise instructor's interview, we extracted the following features necessary for evaluation and used them as input data for machine learning, which was calculated after calibrating the origin position of the coordinates for each subject.

- **Eye line (degree):** Angle calculated from keypoints of nose (Nose, 0; see Figure 2), neck (Neck, 1) and waist (CHip, 8).
- **Heel height when landing (cm):** Maximum value obtained by subtracting the coordinates of ankle (LAnkle, 14) from that of toe (LLToe, 20).

- **Toe height when making contact with the ground (cm):** Maximum value obtained by subtracting the coordinates of ankle (LAnkle, 14) from that of toe (LLToe, 20).
- **Stride length (cm):** Average stride length. Here, for simplicity, we counted how many times the foot makes contact with the ground and divided 5-meter by that number.
- **Gait velocity (m/s):** Average gait speed for each subject.

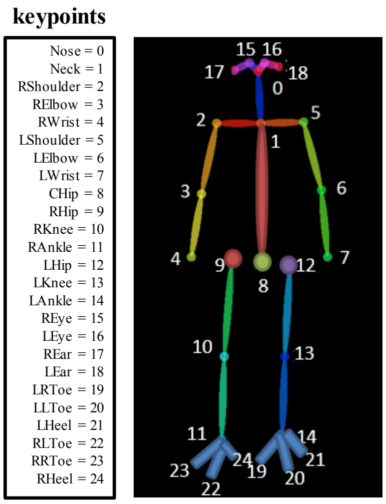
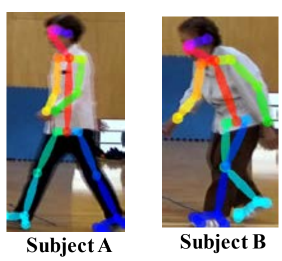


Figure 2: Keypoints detected by OpenPose.

Finally, rehabilitation exercise instructors evaluated the fall risk at 2 levels (Figure 3) for 36 people who are not dementia:
- High (4 people)
- Low (32 people)



Subject	A	B
Eye line (degree)	139	127
Heel height (cm)	10.6	7.0
Toe height (cm)	6.2	6.1
Stride length (cm)	71.4	45.5
Gait velocity (m/s)	1.5	0.7
Possibility of fall risk	Low	High

Figure 3: Example of OpenPose results and fall risk level.

Machine Learning Methods

We evaluated the data of 36 people using 4-fold cross-validation. The learning algorithm used the following:
- SVM (Linear kernel)
- Linear discriminant analysis
- Logistic regression

Result

The results are shown in Table 1. Three people were incorrect answers by all algorithms. There is one case where only Logistic regression fails in the forecast. The predicted result was incorrect because the weight of stride length influenced.

Table 1: The Result of each method.

Learning algorithm	Accuracy(%)
SVM (Linear kernel)	92
Linear discriminant analysis	92
Logistic regression	89

Conclusions

In this paper, we evaluated the fall risk with contactless sensors and OpenPose. As a result, we found that sufficient accuracy can be obtained even with contactless sensors.

In the future, we will expand the data on elderly people and gather additional features to improve prediction accuracy. We interviewed functional training instructors about how to improve accuracy and we found that the feature quantities of balance and flexibility. The feature quantity of the balance can be obtained by taking a video from the front or the back of elderly people. Also, The feature quantity of the flexibility can be obtained by taking a video the pose of seated forward bend.

References

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