IOT Enabled Fall Detection System

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***Abstract* -According to statistics, falls are the primary cause of injury or death for the elderly over 65 years old. About 30% of the elderly over 65 years old fall every year. Along with the increase in the elderly fall accidents each year, it is urgent to find a fast and effective fall detection method to help the elderly fall. The reason for falling is that the center of gravity of the human body is not stable or symmetry breaking and the body cannot keep balance. To solve the above problem, in this paper, we propose an approach for reorganization of accidental falls based on the symmetry principle. We extract the skeleton information of the human body by Open Pose and identify the fall through three critical parameters: speed of descent at the center of the hip joint, the human body centerline angle with the ground, and width-to height ratio of the human body external rectangular. Unlike previous studies that have just investigated falling behavior, we consider the standing up of people after falls. This method has 97% success rate to recognize the fall down behavior**.

Key words: Deep Learning, Fall Detection, Open Pose, Pose Estimation

I. INTRODUCTION

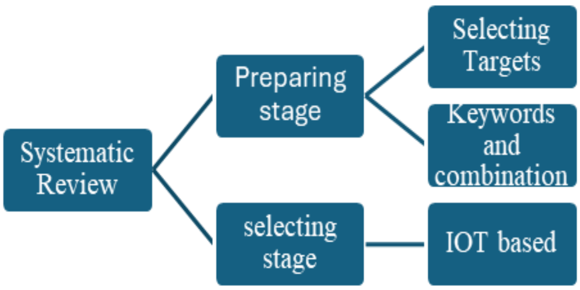
The decline of birth rate and the prolongation of life span lead to the aging of the population, which has become a worldwide problem. According to the research, the elderly population will increase dramatically in the future, and the proportion of the elderly in the world population will continue to grow, which is expected to reach 28% in 2050. Aging is accompanied by a decline in human function, which increases the risk of falls. According to statistics, falls are the primary cause of injury or death for the elderly over 65 years old. About 30% of the elderly over 65 years old fall every year. In 2015, there were 29 million elderly falls in the United States, of which 37.5% required medical treatment or restricted activities for 1 day or more, and about 33,000 people died. The most common immediate consequences of falls are fractures and other long-term ailments, which can lead to disability and loss of independence and psychological fear of falling again. Falls not only make the elderly suffer moderate or severe injuries, but also bring a mental burden and economic pressure to the elderly and their relatives.

This paper proposes a new detection method for falling. This method processes every frame captured by monitoring, which is to use the Open Pose skeleton extraction algorithm to obtain the skeleton data of people on the screen.

II. PROCEDURE

A. Methodology

Through a search of the databases of Pub Med, Google Scholar, and Summon (Ex Libras, Part of Clarivate), we found several publications with articles on falls. To better comprehend the present strategies toward eliminating falls, several kinds of fall were surveyed. We hope this will lead to the creation of algorithms that can be used to develop new systems in the future. Our review of the publications was done in four stages: preparation, searching, selecting, and analysis which is illustrated in Figure.



III.DERIVATION

True positive (TP): a fall occurs, the device detects it. False positive (FP): the device announces a fall, but it did not occur. True negative (TN): a normal (no fall) movement is performed, the device does not declare a fall. False negative (FN): a fall occurs but the device does not detect it. To evaluate the response to these four situations, two criteria are proposed: Sensitivity is the capacity to detect a fall:

$$Sensitivity = \frac{TP}{TP+FN}$$

Specificity is the capacity to detect only a fall:

$$Sensitivity = \frac{TP}{TP+FN}$$

Accuracy is the capacity to correctly detect fall and no fall:

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

IV.ANALYSIS OF THE EXPERIMENTAL RESULTS

Before the final experimental judgment, we analyze the feasibility of the three conditions and the final conditions of standing up after fallingWhen detecting the descending speed of the hip joint center point, the speed of change of each action is shown in Figure 9 below. We can see that the speed of fall and squat can exceed the critical value (0.09 m/s). In other words, only falling and squatting down meet the conditions by decision condition one (the speed of descent at the center of the hip joint).

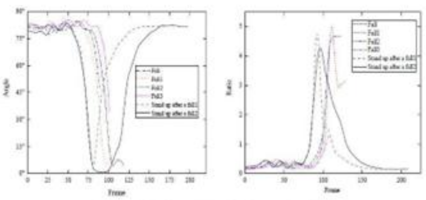


Figure 12. The characteristic of standing up after a fall.

VII. CONCLUSION

Through the analysis of a total of 100 experimental actions, the specific situation is shown in the Table 5 below. In the table, G indicates that the action is correctly identified, × indicates that the action is incorrectly identified. It can be seen that No.1 and No.3 experiments' stooping actions in the non-falling actions are wrongly identified as falling, and only one time in the falling actions is wrongly identified as non-falling.

According to the calculation formula proposed in Section 4.2, the sensitivity, specificity and accuracy are 98.3%, 95% and 97% in Table 6. There are the following reasons for wrong discrimination:

(a) The lack of joint points in skeleton estimation results in incomplete data, which affects the final recognition. (b) The three thresholds selected in the experiment are not necessarily optimal. (c) During the experiment, due to the self-protection consciousness of the experimenter, there are still differences between the recorded falls and the real falls.

V. CONCLUSIONS AND FUTURE WORK

Conclusions

At present, because there are no suitable public datasets of falls, we cannot directly compare our results with previous results in detail. As shown in Below Table . we list the algorithms, classifications, features, and final accuracy of other fall detection technologies. Droghini et al. 30 detected falls by capturing sound waves transmitted on the floor. The accuracy of the experimental results is high, but the experiment uses a puppet to imitate falls, which is still very different from the real human fall. In addition, its detection method is extremely susceptible to interference from external noise, and the available environment is limited. Shahzad et al. [25] make good use of the sensors in smartphones and improves the power consumption of the algorithm, but the phone can always also cause false positives and requires the user to wear the phone. Kepski et al. [44] proposed a fall recognition system based on microwave doppler sensor, which can not only distinguish fall and fall-like movements accurately, but also does not infringe on the human body. The only disadvantage of this method is that the detection range is too small. Quadros et al. [40], the threshold method and machine learning are used to fuse multiple signals to identify falls, which undoubtedly improves the reliability of the recognition results. However, the user needs to wear the device for a long time, and the endurance of the device should also be considered. The method of OpenPose [20,21] can be used to identify the images captured by the camera, which is convenient and fast, and has a broad prospect in video-based methods. Compared with other methods, vision-based is more convenient.

OpenPose gets the skeleton information of the human body, which is convenient and accurate. To some degree, our method not only has high accuracy but also is simple and low cost.

With the popularity of the camera and the clearer quality of the captured image, the vison-based fall detection method has a broader space. In the future, we can carry out the following work:

The environment of daily life is complex, there may be situations in which peoples' actions cannot be completely captured by surveillance. In the future, we can study the estimation and prediction of peoples' behavior and actions in the presence of partial occlusion.

In this paper, the action is identified from the side, and the other directions are not considered. Future research can start with multiple directions recognition and then comprehensively judge whether to fall.

Building a fall alarm system for people. In the event of a fall, the scene, time, location, and other detailed information shall be timely notified to the rescuer, to speed up the response speed of emergency rescue.

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