Fall Risk Reduction for the Elderly Using Mobile Robots Based on the Deep Reinforcement Learning

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Abstract

Slip-induced fall is one of the main factors causing serious fracture among the elderly. This paper proposes a deep learning based fall risk reduction measures by mobile assistant robots for the elderly. We use a deep convolutional neural network to analyze fall risks. We apply a deep reinforcement learning to control robots and reduce slip-induced fall risks of the elderly. The results suggest that the applicability of our method to other cases of the fall and other cases of accidents.

Keywords: Safety, Risk Reduction, Mobile Robot, Deep Learning, Reinforcement Learning.

1. Introduction

An increase tendency of the elderly's accidents is showing no signs of stopping in some countries including Japan.[1-2] In order to reduce the increasing fall accidents among the elderly, we take an approach to use mobile assistant robot. We consider safety in the environments where humans and assist robots coexist in the fields of medical welfare and assist living.

This paper proposes a deep learning based fall risk reduction measures by mobile assistant robots for the elderly. First, we collect preparatory data regarding past incidents and accidents data as input data to analyze fall risks and to learn examples of risk reduction measures. Second, we use a deep convolutional neural network[3] to analyze fall risks of the elderly. Third, we apply a deep reinforcement learning[4-5] to control mobile robots and reduce slip-induced fall risks of elderly. Moreover, we evaluate the effect of risk reduction.

2. Risk analysis

The risk analysis is carried out through methods such as FTA (Fault Tree Analysis),[6] HAZOP (Hazard And Operability Study),[7-8] and FMECA (Failure Modes Effects and Criticality Analysis).[9] Conventional risk analyses conducted manually or partially use a probability calculation tool when employed in applications such as system safety requirement analysis or design. This type of analysis has the following limitations:

- Failures to identify hazards may occur depending on the proficiency of the safety management officers, that is, their experience and capability,
- Risk analysis procedures are complex and require a specific number of man-hours depending on the scale of the assessment.

Most analyses and assessments are carried out offline based on prior information and require time to be conducted. The results are not immediately available. Therefore, the measures of risk reduction are often delayed, and it becomes difficult to respond promptly and flexibly in continually changing situations.

In this paper, we use online real-time risk analysis based on the deep convolutional neural network. The input is environmental sensing data aimed at detecting HEs (Hazard Elements), IMs (Initiating Mechanisms, triggers of the accident), and T/T (Target and Threat) in the. Ericson's Hazard Theory.[10] According to the Ericson's Hazard Theory, the accident (mishap) occurs when HE, IMs and T/T are appeared at the same time in specific timing. The sensing data is mainly time-series images of the environment and distance information to the objects and parts of human body.

The main output is the result of risk analysis and the level of risk as quantitative information. The risk is presented with following formula:

$$Risk = S * Ph. \tag{1}$$

$$Ph = F + Ps + A \tag{2}$$

. Eq. (1) shows that the risk is multiplication of the severity of the harm (S) and the probability of the harm (Ph). Eq. (2) displays the probability of the harm (Ph) is the combination of following: frequency of exposure to hazards (F), the probability of occurrence of hazardous event (Ps), the possibility of avoiding or limiting the harm (A). Furthermore, according to the result of risk analysis, we generate a painting of the future by blending a representative hazardous image per each risk category with a current image.

3. Risk reduction

In general, about the safety of machinery, risk reduction carries out through methods such as inherently safe design measures, safe guarding implementation of complementary protective devices and information for use.[11-13] In addition to the above, risk reduction learns from the previous incidents and accidents, [14] which improves the environment, for example, removes hazard elements, supports avoiding hazardous situation and stops the trigger of incidents and accidents.

This paper proposes online real-time risk reduction based on the deep reinforcement learning. Figure 1 illustrates that inputs are following environmental data: the elderly's outer factors and inner factors. Outer factors are some sensing data, for example, images from stereo camera and laser range finder. Inner factors are elderly's physical condition, for example, breathing. The other input is the risk level that is the result of risk analysis as a negative reward.

This deep neural network is trained with the Q-learning algorithm, [4-5] with Adam[15] for optimization of parameters. Moreover, this network uses batch normalization for improving the learning rate and robustness of initial value of weight.[16]
The output is the action as the risk reduction measures.

4. Experiment

We performed an experiment on a simulation. Figure 2 shows a visualization of an environment and an agent. A scenario is that an elderly person who is assisted by mobile robot goes to the toilet at a certain interval in the hospital. Sometimes the floor is partially wet. The mobile robot (agent) assists preventing from slip-induced fall for the elderly.

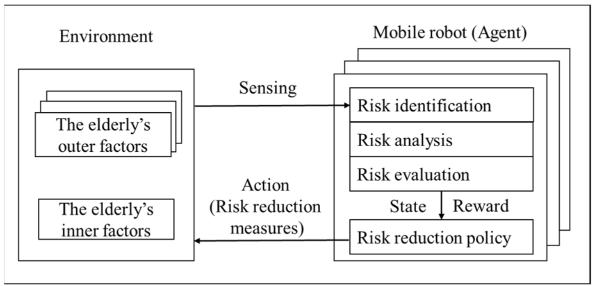

Fig. 1. Reinforcement learning for fall risk reduction of the elderly.

Figure 3 presents a process how the reward changes during training on the simulation. The increase of the reward indicates the reduction of the risk. We evaluate the effects of our approach through these change of graphs. We obtained the result of simulation that the agent is able to act reducing slip-induced fall risks automatically.

Figure 4 depicts an example of the deep neural network model generating risk reduction measures. We apply the combination of 3-streams (the current flow, the chaging

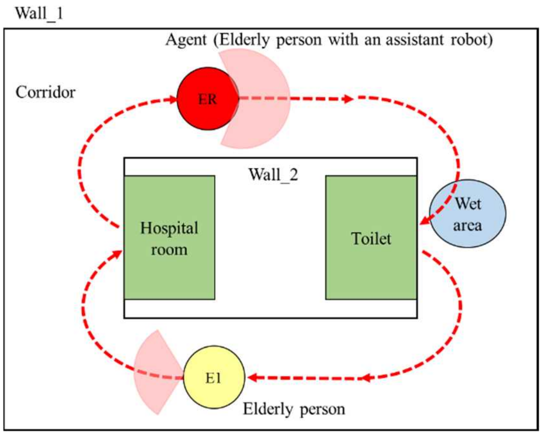

Fig. 2. A simulation environment of experiments. ER is an elderly person assisted by a robot as an agent. E1 is another elderly person. From a hospital room, ER goes to the toilet at a certain interval by walking on the corridor between Wall_1 and Wall_2. E1 also goes to the same toilet. Sometimes it is wet on the floor and ER detects wet area. The fan-shaped area shows the sensing rage of ER and E1.

flow and the changing rate flow) deep convolutional neural network and full connection network to determine the risk reduction measures. The data of input layer composes state and reward vectors.

5. Conclusion

In this paper we proposed a fall risk reduction measures for the elderly using mobile robots based on the deep reinforcement learning, and have presented its usability. The results of experiments suggest that the applicability

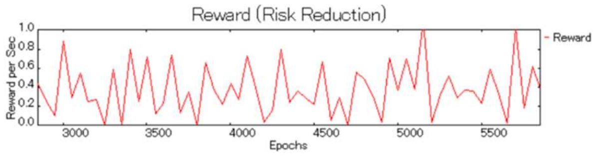

Fig. 3. Change of reward during training on the simulation.

of our method to other cases of the fall and other cases of accidents.

References

1. Takaaki Namba, and Yoji Yamada, A study on an assistance by mobile robots in preventing the elderly from falling, Proceedings of annual meeting of the the Japan Society of Mechanical Engineers 2015, Paper No. J1630205, 2016 (in Japanese).
2. Takaaki Namba, and Yoji Yamada, A study on an assistance by mobile robots in preventing the elderly from falling (Deep Convolutional Neural Network for Fall risk Analysis), *Proceedings of annual meeting of the the Japan Society of Mechanical Engineers 2016*, Paper No. J1640304, 2016 (in Japanese).
3. Alex Krizhevsky, Ilya Sutskever, and Geoff Hinton. Imagenet classification with deep convolutional neural networks, *In Advances in Neural Information Processing Systems 25*, (2012), 1106–1114.
4. Christopher J. C. H. Watkins and Peter Dayan, Q-learning, *In Machine Learning*, vol. 8, (1992), pp. 279-292.
5. Mnih, Volodymyr et al. Playing Atari with Deep Reinforcement Learning". *In:CoRR abs/1312.5602*,(2013).
6. C. Ericson, Fault tree analysis – a history, *In:17th International System Safety Conference. Unionville, VA*, (1999), pp.1-9.

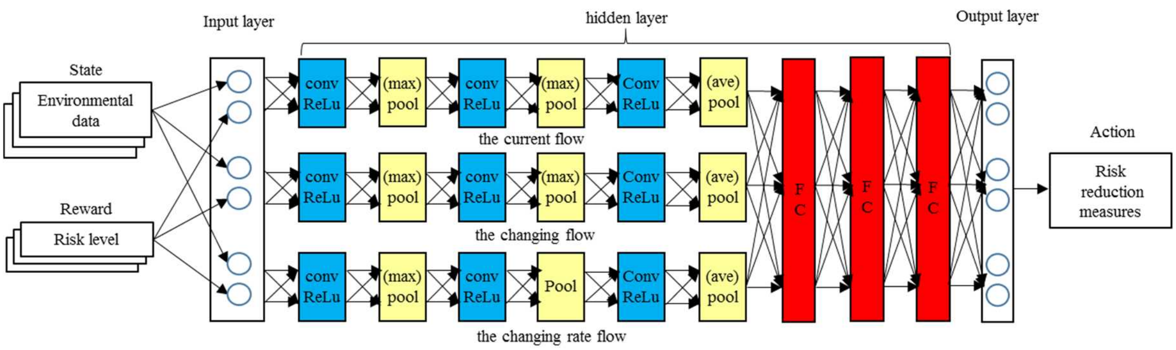

Fig. 4. A deep neural network model generating a risk reduction measures.

7. Faisal I Khan, S.A Abbasi, Techniques and methodologies for risk analysis in chemical process industries, *Journal of Loss Prevention in the Process Industries, Vol.11, Issue 4*, (July 1998), pp.261–277
8. Jordi Dunjóa, Vasilis Fthenakis, Juan A. Vílchez, Josep Arnaldos, Hazard and operability (HAZOP) analysis, *A literature review, Journal of Hazardous Materials, Vol. 173, Issues 1–3*, (15 January 2010), pp.19–32
9. MIL-STD-1629A, *Military Standard, procedures for performing a Failure Mode, Effects and Criticality Analysis*, (Department of Defense, Washington, DC, 1980).
10. Crifton A. Ericson II, *Hazard Analysis Techniques For System Safety, Second Edition*, (John Wiley & Sons, Inc., 2016).
11. ISO12100, Safety of machinery – General principles for design – Risk assessment and risk reduction, 2010.
12. IEC61508-ed2, Functional safety of electrical /electronic / programmable electronic safety-related systems, 2010-04.
13. ISO13482, Robots and robotic devices -- Safety requirements for personal care robots, 2014.
14. David L. Cooke, Learning from Incidents, System Dynamics Society, (2013)
15. Diederik Kingma and Jimmy Ba., Adam: A Method for Stochastic Optimization, *3rd International Conference for Learning Representations (ICLR), San Diego*, (2015)
16. Sergey Ioffe and Cristian Szegedy, Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, *Journal of Machine Learning Research*, (2015)