Emergency System for Elderly – a Computer Vision Based Approach

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Abstract. Elderly tend to forget or refuse wearing devices belonging to an emergency system (e.g. panic button). A vision based approach does not require any sensors to be worn by the elderly and is able to detect falls automatically. This paper gives an overview of my thesis, where different fall detection approaches are evaluated and combined. Furthermore, additional knowledge about the scene is incorporated to enhance the robustness of the system. To verify its feasibility, extensive tests under laboratory settings and real environments are conducted.

Keywords: ambient assisted living;fall detection;elderly;risk detection; autonomous system

1 Introduction

Emergency systems for elderly contain at least one sensor (button or accelerometer), which has to be worn or pressed in case of emergency. These emergency call buttons are provided by care taker organizations having the main drawback that no information about an occurred incident prior the button press is available. Moreover, people have to wear these buttons which they tend to forget or even refuse. In case of an emergency and if elderly are able to press the button, they have to tell the operator, which kind of incident happened. If the elderly is not able to talk to the operator for any reason, there is no information about the type of incident at all. This causes false alarms as well as ambulance deployments, although there is no emergency situation at all. To ensure the detection of emergency situations where the elderly is not able to actively raise an alarm (e.g. due to the lost of consciousness), sensors acting autonomously are needed.

Autonomously acting sensors are used in the field of smart homes to fulfill core functions defined in [10]: the control of the system, emergency help, water and energy monitoring, automatic lighting, door surveillance, cooker safety, etc.. Due to various reasons summarized in [9], smart homes are not established yet. One of the reasons mentioned in [9] are costs: it is easier and less expensive to integrate smart home technology into new buildings than it is for already existing buildings. This results in the demand of a robust system, which can be integrated into existing buildings. Moreover, one of the outcome of the former project MuBisA is that elderly accept technical assistance only if the system is not discernible for third persons. For these people, assistance means covert assistance in physical or intellectual impairment as long as possible, being hidden especially when it comes to visitors not belonging to the family or the innermost circle of friends. A small, low–key system would fulfill that demand.

Considering these facts, a computer vision approach is feasible as it is able to overcome the limitations of other sensor types [11]. Furthermore, not only falls can be detected but also other events where help is needed (e.g. fire, flooding,. . .). By the use of a vision based system the detection of emergency situations is done by software, meaning that this system is extendable as only the algorithms need to be extended or adopted. A wide variety of computer vision algorithms for different applications exist (e.g. [5–8]), but there is no "perfect" algorithm for detecting emergencies in elderly's homes yet.

As falls are considered to be a major risk for elderly, there has been done research on automatic fall detection [4]. Not only the fall itself but also the consequences of a fall are a great risk for elderly. [1] have shown that getting help quickly after a fall reduces the risk of death by over 80% and the risk of hospilization by 26%.

The rest of this document is structured as follows: Sect. 2 gives an overview over the State–of–the–Art. The methodology is shown in Sect. 3, an evaluation can be found in Sec. 4. Finally, a conclusion is presented in Sect. 5.

2 State–of–the–Art

In general there are two main approaches to detect falls – either elderly have to wear sensors (e.g. accelerometers, [3]) or falls are detected by computer vision systems (e.g. [5–8]). For our work, only the latter are of interest as we are not dealing with any kind of wearable sensors.

The general methodology of a fall detection systems is described in [4]. At first, people needs to be separated from the background. Therefore, motion detection and background subtraction is used. After the human is detected in the video, different kind of fall detection approaches are used. These approaches can be distinguished between 2D and 3D approaches. To be able to reconstruct a scene in 3D, a calibrated camera setup is needed.

When using a 2D approach, only limited information about the person is available. The shape of the person implies the orientation and thus can be used to distinguish whether a person is in an upright position or not. The bounding box aspect ratio (width to height ratio) to detect falls is used in [5]. If people are in an upright position, the ratio of the height to the width of the bounding box is bigger than one. If a fall occurs, the ratio rapidly changes to a value smaller than one. Another approach presented in [6] does not use the information of a bounding box but of an approximated ellipse. Falls are detected by analyzing the orientation of the ellipse.

Approaches making use of 3D information try to reconstruct humans from silhouettes gained by different camera views [7]. Hence, the human is represented by the use of voxels allowing to identify different states (upright, on–the–ground and in–between). Another approach presented in [8] uses 3D information to track the head of the person and to obtain its trajectory. Not only the head position but also the velocity of movement is taken as an indicator for falls as the velocity of movement during a fall is typically higher than during usual activities of daily living.

3 Methodology

Systems to detect falls using different approaches (e.g. 3D head tracking [8], aspect ratio of bounding box [5]) already exist. Hence, the use of these approaches and their results are evaluated. Based on this evaluation, improvements and combinations of feasible approaches are developed. Furthermore, additional knowledge of the scene is taken into account and is integrated to enhance the overall stability of the system. As the error rate of such systems should be low, not only the fall itself but also the whole environment has to be considered due to the similarities in movement between falls and other activities of daily living. Hence the structure of the scene needs to be taken into consideration, facilitating an overview and thus enabling decision making to be more robust.

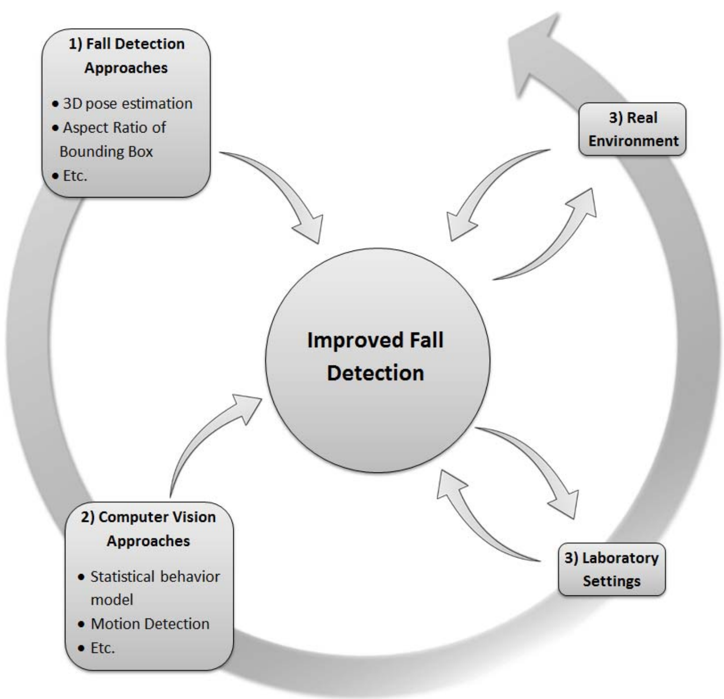

Fig. 1. Methodology

Due to the combination of different approaches, the system does not rely on one single approach only which increases the performance. To verify these assumptions, the algorithms are evaluated under laboratory settings as well as in real environments (i.e. elderly in their homes) comprehensively. Figure 1 shows an overview of the methodology: 1) different fall detection approaches are evaluated, 2) fall detection approaches are combined together with additional scene knowledge, 3) comprehensive evaluation and verification is done under a) laboratory settings and b) in real environments.

4 Evaluation

Our developed system is a specific solution for indoor environments. Thus it is able to handle challenges which can be typically found in indoor environments like illumination changes due to switching the lights on or off as well as movements without any information (e.g. the movement of curtains due to wind) which effects the motion detection. These factors need to be taken into account to develop a robust system. Therefore it is not sufficient to test the developed algorithms at laboratory settings, but also in real environments comprehensively.

The aim of our work is to ensure that critical situations like falls are detected while having a low false alarm rate. Hence, the developed algorithms need to be adopted to the use in elderly's homes. Currently no known system is able to detect all kinds of falls correctly as the movement during a fall can be mistaken with other activities of daily living (e.g. sitting down, lying on the bed, etc.). Within this work a robust method which is able to distinguish between activities of daily living and falls is developed. Therefore not only the development of one specific fall detection approach leads to success, but a combination of different fall detection approaches together with incorporated additional knowledge about the scene (e.g. a statistical behavior model introduced in [2]).

Figure 2 shows anonymized snapshots of the system. Since we use cameras within the homes of elderly, privacy and the protection of data is very important. To ensure the dignity of elderly, the system anonymizes the video stream automatically.

Fig. 2. Anonymized snapshots taken by the system

5 Conclusion

To be able to develop an efficient and robust vision based fall detection system, a combination of different approaches is feasible. The integration of other computer vision approaches like behavior models enhances the overall robustness of the system furthermore. Nonetheless, the system has to be evaluated within real settings as well. Only this ensures that all factors (e.g. moving curtains, rapidly changing light conditions, etc.) are considered.

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