A Real-time Fall Detection System for Maintenance Activities in Indoor Environments *

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Abstract: A real-time, multi-camera incident detection system for indoor environments is presented in this paper. The paper focuses on the detection of fall incidents while it highlights the leverage that such a system can provide to the human resources department of a shop-floor especially referring to the maintenance procedures. The proposed detection method extracts features that characterize a falling person’s trajectory, like vertical velocity and area variance, while the fall is described by Hidden Markov Models (HMM). The system utilizes only privacy preserving sensors. Experimental results illustrate its efficiency.

Keywords: Incident detection, fall, shop-floor, Hidden Markov Models, human resources.

1. INTRODUCTION

Maintenance is not an easy task, especially when maintenance technicians are prompted to approach remote or dangerous areas due to irritant chemical agents, climatic conditions etc. Detection of risky or dangerous incidents in an indoor environment, such as a shop floor where maintenance activities are ongoing, is a practical problem highly affecting workers’ safety. A system monitoring and recognizing such events could automatically trigger the appropriate alarm so that measures dealing with the incident can be taken immediately. A Human Resources Management software tool, connected to the Computerized Maintenance Management System (CMMS) or the Enterprise Asset Management (EAM) can react fast and cope with the event depending on its importance.

An essential component of such system is a fall detector. Falls could be caused either from just a simple stumbling, could be originated from a health problem (faint, heart attack) or even be the result of an accident, such as being hit by an operating device. Furthermore, they could occur in a restricted or dangerous area increasing the importance of their immediate detection.

Fall detection has preoccupied researchers for many years. Existing approaches can be divided in two groups: techniques using non-vision sensors (Wu and Xue (2008), Shany et al. (2012)), especially accelerometers, and exclusively vision based methods. Since wearable equipment can be annoying for workers, vision based methods, that are less intrusive, are preferred. Furthermore, depth sensors constitute a good solution that takes care of the ethical and legal issues of individual privacy. Previous work includes approaches utilizing the distance from the top or the centroid of a person to the floor as a basic criterion for fall detection (Diraco et al. (2010), Kepksi and Kwolek (2014)). In particular, in Diraco et al. (2010), a certain threshold to the floor and a specific time period of immobility on the floor are used as criteria for fall detection while in Kepksi and Kwolek (2014) a k-NN classifier trained on features such as head-floor distance, person area and shape’s major length to width is utilized. Moreover, there are methods analysing the person’s movement in a world coordinate system(Stone and Skubic (2014), Zhang et al. (2012b), Mastorakis and Makris (2014)). In this category, Stone and Skubic (2014) propose an ensemble of decision trees for the fall’s confidence computation, whereas in Zhang et al. (2012b) a Bayesian framework is utilized. In Mastorakis and Makris (2014) the velocity which is measured by the expansion and contraction of the tracked person’s 3D bounding box constitutes the criterion for fall detection. Finally, other techniques utilize skeletal joints tracking in order to achieve fall detection (Zhang et al. (2012a), Bian et al. (2014)). A good survey on vision based fall detection can be found in Zhang et al. (2015).

This paper extends previous work (Krinidis et al. (2014)) on a real-time, multi-space, multi-camera tracking system to a fall detection system with all the deriving qualities, i.e. monitoring any area regardless its size by the use of multiple depth sensors that retain workers’ individual privacy. The introduced detection system is based on key features that characterize a fall, such as vertical velocity and area variance, while falling process is modelled by HMM. Furthermore, the system produces alarms that can be used by the human resources department of a shop-floor, triggering immediate response. To our knowledge, it is the first work presenting a system that combines all these characteristics to support the maintenance operation and in general.

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To sum up, the main contributions of this paper are:
(1) The introduction of a real-time, multi-space, multi-camera fall detection system.
(2) The fall process modelling by an HMM based on the falling person’s velocity and area variance from top view.

The remainder of the paper is organized as follows: section 2 describes the methodology of the presented approach, section 3 analyses the importance and leverage that a system like the proposed one can offer to the human resources department of a shop-floor while section 4 includes the experimental results. The paper concludes with discussion on the proposed approach.

2. INCIDENT DETECTION METHOD

The presented incident detection methodology comprises three steps: 1) detection and tracking of moving items, 2) extraction of event features that are indicative of the items’ state, e.g. a worker’s fall need further processing. 3) An HMM method that recognizes the occurring incidents based on the event features.

2.1 Detection and tracking of moving items

In the first stage of the proposed method, a real-time, robust tracking system is used (Krinidis et al. (2014)). The utilized camera calibration algorithm allows the use of multiple cameras that refer to a common coordinate system located on the architectural map of the shop-floor’s building. This fact enables the monitoring of any area regardless its size. Furthermore, partial occlusions are handled by deploying a virtual top-view camera based on calibration data. Thus, the overall detection - tracking procedure remains unaffected since it is performed on the horizontal plane. In addition, dynamic changes of the environment can be encountered by a dual-band algorithm that incorporates to the background low objects, e.g. a chair, in a small period of time while retains for a longer period higher objects, such as humans.

2.2 Extraction of event features

While the detection of an event like intrusion to a forbidden area is straightforward once tracking is achieved, incidents such as a worker’s fall need further processing. Therefore, event features, indicative of the tracked items state, are extracted.

For the fall detection incident the aforementioned features are:
(1) Vertical velocity $v$. A characteristic feature of a fall is the vertical velocity of the tracked person’s highest point. Nevertheless, depth sensors often provide noisy data that affect the height’s value. Thus, the mean velocity of a constant time window is calculated while a six order, low pass FIR filter with cut-off frequency 3Hz is applied on the corresponding heights (the order and cut off frequency of the filter were determined experimentally). The velocity’s formula is:

$$v = \frac{1}{t_e - t_0} \int_{t_0}^{t_e} h'(t) \, dt,$$

where $h'(t)$ represents the tracked person’s height derivative (for brevity it will be referred as $h$), $t_e$ is the current time and $t_e - t_0 = C_T$ is a constant time window.

There are cases where partial occlusion might abruptly cut a big portion of the worker’s blob upper part. In this case velocity forms a step signal and can lead to false alarms for fall detection. In order to deal with this phenomenon, once a step signal is detected, the velocities that include it in their calculation are set to zero.

(2) Area variance $\sigma^2$. As a person is falling, its area, measured from a top view, is gradually augmenting. This feature is captured by the variance of the area, in the same time window as velocity, in order to be independent from the initial area of a person before falling and relatively robust to noise. The area variance formula is the following:

$$\sigma^2 = \frac{1}{t_e - t_0} \int_{t_0}^{t_e} (A(t) - \int_{t_0}^{t_e} A(t') \, dt')^2 \, dt,$$

where $A(t)$ represents the area of the tracked human calculated from top view.

(3) Height $h$. Apart from its importance to vertical velocity calculation, the value of the highest point of the person under detection facilitates the avoidance of false alarms. For example, the final height of a fallen person cannot be higher than 1 meter.

2.3 Incident recognition

A three state Markov model that takes into account the aforementioned event features is used in order to achieve fall detection. The first state ($S_1$) refers to a non-falling state, e.g. a human walking or standing. The second state ($S_2$) represents the actual fall which is characterized by highly decreasing vertical velocity (when the height decreases the velocity takes negative values) and augmenting area variance. The third state ($S_3$) signifies the end of the fall and declares the detection of the incident. The transition probabilities are based on the event features and are defined in the following matrix:

$$P = \begin{bmatrix} \frac{(1-F)(1-u)}{1} & F & 0 \\ (1-F)u & (1-F)u & 0 \end{bmatrix},$$

where

$$F = \frac{1}{1 + e^{\sigma^2 + T}},$$

and

$$u = \begin{cases} 0, & H_T - h \geq 0 \\ 1, & H_T - h < 0 \end{cases},$$

where $T$ is a constant defined by training and $H_T$ is a constant threshold.

The probability $F$ constitutes a sigmoid function that favours with high values close to 1 cases with high (negative) vertical velocity and high area covariance, i.e. cases that correspond to the state of falling. Moreover function $u$ declares that state $S_3$ that signifies the detection of the fall cannot be reached if the fallen person is not below a loose threshold $H_T$. 

$$\frac{d}{dt} h = \frac{1}{t_e - t_0} \int_{t_0}^{t_e} \frac{h'}{h} \, dt,$$
3. EVENT DETECTION AND HUMAN RESOURCE MANAGEMENT

The incident detection methodology described refers mainly at this point at the detection of a person from the maintenance team entering in a restricted area and of falls of personnel. The ability to detect such types of incidents can be capitalized for the improvement of human resources (HR) management and allocation. It is possible to obtain information about personnel’s presence and movement at the shop floor by using the depth cameras or even with small wearable devices embedded in the suit of the maintenance technicians. This knowledge can be not only useful, but crucial in the case of a severe accident during the implementation of maintenance works. Tools such as those presented here offer a great potentiality for incident management and the ability to improve the management and safety of the maintenance operation.

When the analysis shows a potential event, based on specific features, the incident can be fed as a trigger to an automated system to assess its importance. The system could detect the presence of maintenance -in our case- personnel at a restricted area. In the case of ongoing corrective or preventive maintenance activities at hazardous areas, this information can be very important in order to remotely inspect and supervise such an endeavour. It also enables allocating the minimum of personnel in the problematic area.

It is of interest to more carefully examine the possibilities deriving from the detection of a fall of a person in a working environment in industrial manufacturing facilities. Several alternative cases can be discussed to support this point (Fig. 2). In case A there is a person who falls and then gets up. Here, there is no need to take immediate action. However, at the backlog of health and safety issues this could remain as a near-accident to be investigated. It could lead to the improvement of the facilities and the removal of potential causes of small accidents. In case B1 a person falls and does not get up in an area where no special conditions are imposed or dangerous material are used. The detection of such an incident triggers an alarm or event to the HR management tool for sending at the specific site a member of the team to check on the well-being of their co-worker. Thus, it would facilitate the provision of immediate assistance to the person hurt. In the case B2 a person falls and does not get up in a dangerous area (climatic conditions that do not allow for long human presence, use of chemicals, leakage of chemicals, in the vicinity of machinery with moving parts etc.). It is imperative then for the system to rise an alarm for human intervention as soon as possible, having as a first target the removal of the hurt person. The quick response can make a big difference in this case. This is the reason why the common practice is that the maintenance personnel involved in such tasks has been training in providing first aid.

In general, each incident detected has the potential of being assessed based on a set of criteria such as the following: the area where the incident is indicated, the status of the area (restricted to all, work ongoing, under maintenance, accessible to a specific group of people), the condition of the area (ongoing production process, leakage of material detected, there is knowledge of an accident that has occurred there, explosive environment etc.). Consequently, the information deducted form the described method can be proven extremely valuable for human resource management of the maintenance team, especially coupled with health and safety issues.

4. EXPERIMENTS

4.1 Dataset

To evaluate the proposed fall detection method a dataset with 70 events performed by 7 different persons was acquired. These events include 40 falls and 30 events with features similar to falling, such as a person bending to tie his shoes or to pick up an item from the floor (Fig. 3). These events are examined in order to test the robustness of the algorithm in cases that affect the event features that determine the transition to the HMM states, i.e. vertical velocity and area variance. Furthermore, the participants were allowed to fall in ways that felt natural to them, leading to a variety of falls, e.g. fall forwards, backwards, sideways, fall while walking, like stumbling, or while standing, as fainting. Finally, since the incident detection scenario takes place in a shop-floor, there were people walking or standing in the monitoring area during the experiments.
Fig. 3. Events included in the dataset. The first two rows correspond to fall events, the third and fourth row to bending and picking up items while the last to bending in order to tie shoes.

The experiment was conducted in two different working environments: CPERI and ITI institutes of CERTH in Greece. In both cases two depth sensors (Kinect cameras for Xbox360) monitoring subsequent areas were used.

4.2 Event features processing

As it is already mentioned in section 2.2 the noisy data acquired from depth sensors can lead to false alarms. Apart from FIR filtering that smooths the height (Fig. 4), the algorithm detects step signals occurring (Fig. 5) either from occlusions with real items or sometimes, with holes in the depth images that can be caused by shiny or black items. Such an example can be seen in Fig. 5. The abrupt height change from 1200mm to less than 600mm indicates a step signal caused by occlusion, hence it should not be mistaken as a fall. Thus, the two aforementioned measures prevent big deviations between the calculated velocities and their actual values.

In Fig. 6 graphs of the event features during a fall are depicted. As it can be seen in the height graph (Fig. 6.a) the tracked person is initially in a standing position, then falls, remains lying on the ground for a while and finally stands up. Velocity and area variance values change drastically because of the fall (Fig. 6.b and Fig. 6.c) but with a very small time delay (less than a second) due to averaging (section 2.2). Moreover, Fig. 6.d depicts the probability $P$ that is crucial for the HMM’s transitions. Its value raises fast due to fall, then decreases and remains low for the time the person is lying on the floor and finally augments, remaining below 0.5, while the person rises.

At this point, it should be mentioned that sensors’ frames were acquired with 15 fps (this value depends on the utilized computer computational power). Furthermore, time window $C_T$ is about 0.65 seconds (so that about 10 different values are averaged for the velocity and area calculation) , threshold $T$ is $10^{-6}$ (based on a training set of 10 falls) while $H_T$ is 1 meter.

4.3 Experimental results

| True Positives | True Negatives | False Positives |
|----------------|----------------|-----------------|
| 40             | 28             | 2               |

Table 1. Fall Detection Results

| Precision  | Recall | F1-score |
|------------|--------|----------|
| 95.24%     | 100%   | 97.36%   |

Table 2. Fall Detection Performance

The proposed algorithm was tested in more than 50000 frames including falls, events similar to falls but also people walking or standing in the monitored area. All the 40 falls were detected correctly, while there were 2 false positives in the whole dataset. These false alarms corresponded to 2 out of the 30 similar to fall events where a participant bended and picked up the mattress used for falls. It has to be mentioned that this task was
replicated 5 times but only in 2 of them produced false alarm. Fall detection results on the acquired dataset are summarized at tables 1 and 2. The recall rate is 100% while precision is 95.24% leading to a rather high F1-score that equals 97.56%. The results refer only to falls and similar to fall events. Nevertheless, people just walking or standing at the monitoring area during the experiments did not produce any false positives, even though they were not taken into account at the results. Furthermore, the algorithm was tested in 15 falling cases of an on-line dataset (http://fenix.univ.rzeszow.pl/~mkepski/ds/uf.html) and detected them successfully without any false alarms.

5. CONCLUSION

This paper presents a real-time, multi-camera incident detection system for shop-floor applications. The proposed system can be a great asset for maintenance activities especially if the take place in remote or dangerous areas since it can notify of accidents or hazardous events. Thus, the appropriate coping mechanism can be immediately triggered and deal with the incident. Furthermore, the proposed system provides a sense of safety to workers without entranching their privacy rights since only depth sensors are utilized.

The paper focuses on the detection of fall incidents. Fall process is modelled by HMM based on features that characterize a fall event such as vertical velocity and area variance from top view of the tracked person. Experimental results are very promising since only cases of bending to pick up huge items, such as the mattress, caused false alarms. Nevertheless, such cases are probably rare in a shop-floor. Moreover, all the real falls were detected without misses. Incorporation of more incidents to the presented system, like a falling item or collision events, are planned as future work.

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