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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, 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:

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

where $h^{'}(t)$ represents the tracked person's height derivative (for brevity it will be referred as h), t_c is the current time and $t_c - t_0 = C_T$ 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 σ^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:

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

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:

$$P = \begin{bmatrix} \text{(1-}F\text{)} & F & 0 \\ \text{(1-}F\text{)(1-u)} & F & \text{(1-}F\text{)u} \\ 1 & 0 & 0 \end{bmatrix}, \qquad (3)$$

where

$$F = \frac{1}{1 + e^{v\sigma^2 + T}}, \qquad (4)$$

and

$$u = \begin{cases} 0, & H_T\text{-h} \geq 0 \\ 1, & H_T\text{-h} < 0 \end{cases}, \qquad (5)$$

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.