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A Data-Driven Monitoring Technique for Enhanced Fall Events Detection

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Abstract: Fall detection is a crucial issue in the health care of seniors. In this work, we propose an innovative method for detecting falls via a simple human body descriptors. The extracted features are discriminative enough to describe human postures and not too computationally complex to allow a fast processing. The fall detection is addressed as a statistical anomaly detection problem. The proposed approach combines modeling using principal component analysis modeling with the exponentially weighted moving average (EWMA) monitoring chart. The EWMA scheme is applied on the ignored principal components to detect the presence of falls. Using two different fall detection datasets, URFD and FDD, we have demonstrated the greater sensitivity and effectiveness of the developed method over the conventional PCA-based methods.

Keywords: Fall detection, Dimensionality reduction, SPC charts, Visual surveillance, Image processing.

1. INTRODUCTION

Falls is a major problem confronting seniors resulting in injuries and generating a significant obstacle in independent living of the elderly people (Ageing and Unit, 2008). According to (Igual et al., 2013), at the minimum one-third of seniors aged 65 years and over fall at least one time a year. The consequences of falls include fractures, loss of independence, and even death. Additionally, falls increase healthcare costs due to increased physician visits, emergency room use and hospitalization. Indeed, a survey showed that falls will increase medical care expenditures by \$43.8 billion by 2020 (Soriano et al., 2007; Delahoz and Labrador, 2014). Therefore, providing strategies to detect and prevent falls is crucial to enhance people's lives. Over the past four decades, there has been resurgent interest in human fall detection for human health safety (Rougier et al., 2011; Hazelhoff et al., 2008; Vishwakarma et al., 2007; Liu et al., 2010; Rimminen et al., 2010; Li et al., 2012).

The need for fall detection methods that can accurately and quickly detect falls has recently become even more important than ever before (Mubashir et al., 2013). Over the past few decades, several fall detection techniques have been developed (Mubashir et al., 2013). Researchers and engineers have developed several fall detection techniques (Mubashir et al., 2013) that generally can be classified into two main families: non-computer vision and computer-vision-based techniques (Mubashir et al., 2013; Rougier et al., 2011; Aslan et al., 2015). In fall detection applications, non-computer vision approaches are usually related on the information captured by different sensors such as acceleration sensors and floor vibration sensors. Techniques in this category are mostly based on sensors information, such as sound signals, vibration and human body movement for detecting a fall (Liu et al., 2010; Rimminen et al., 2010; Li et al., 2012). The main limitation of these methods is that: measurement sensors are easily impacted by noise in the living environment and therefore affect the performance of fall detector by increasing the the number of false positives. To surmount these limitations, computer vision-based fall detection techniques, on the other hand, rely on information obtained from images and videos. Increasing attention, over recent years, has been accorded to computer vision-based fall detection techniques (Rougier et al., 2007; Auvinet et al., 2011; Kwolek and Kepski, 2015). In this regard, some of the research efforts made by previous researchers deserve mentioning. Rougier et al. extracted the body's shape change information and the head's velocity, and an appropriate threshold was set manually to distinguish between non-fall and fall activities (Rougier et al., 2007). However, these methods produce an important false alarms (since several fast sitting activities were misclassified as a falls) and the performance was strongly depended on the threshold value. Auvinet et al. proposed another method for fall detection using the reconstructed 3-D shape of a monitored person (Auvinet et al., 2011). This technique provide satisfactory performance, however it requires at least four cameras and graphic processing unit for computation. Liao et al. introduced the integrated spatiotemporal energy map to characterize the fall activities (Liao et al., 2012). In (Lee and Mihailidis, 2005), Lee et al. used carefully engineered features for fall detection, such as silhouette features, lighting features, and flow features to separate between people and multiple moving objects. Anderson et al. extracted a bounding box and motion features from successive silhouettes frames (Anderson et al., 2006).

Statistical process control (SPC) is a major tool for checking the process quality by identifying abnormalities and to make sure that it works in healthy condition (Montgomery, 2005; Kadri

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et al., 2016). In SPC charts, observations are obtained from the process and the values of some statistics are computed and plotted over time. To monitor several different process variables in the same time multivariate statistical monitoring charts were developed (Qin, 2003; Abdi and Williams, 2010; MacGregor and Kourti, 1995; Qin, 2003). This paper addresses the problem of detecting fall events within a statistical framework. The monitoring strategy developed was able to provide early alert mechanisms in the event of fall situations. The major contribution of this study is to exploit the advantages advantages of the exponentially weighted moving average (EWMA) chart and those of principal component analysis (PCA) modeling for enhancing detection of fall events. Such a choice is mainly motivated by the greater ability of the EWMA metric to detect small changes in process mean, which makes it very attractive as anomaly detection chart. In fact, the objective is to extend the abilities of the univariate EWMA monitoring chart to deal with multivariate processes. In the proposed approach, EWMA monitoring chart is applied on the ignored principal components (which have smallest variances) to detect the presence of anomalies. These new detectors are expected to provide better anomaly detection in the process mean at multivariate data sets by reducing the rate of missed detections and false alarms that are associate with PCA monitoring methods.

The following section presents the image processing steps. Section 3 briefly review how PCA anomaly detection is performed, and Section 4 introduces the EWMA monitoring chart and its use in anomaly detection. Next, the proposed approach for fall detection is outlined in Section 5. In section 6, the performances of the proposed method are evaluated and compared to that of the conventional PCA method. Finally, Section 7 concludes this study, paving the way for future research.

2. PREPROCESSING AND FEATURE EXTRACTION

Fall detection strategy based on visual monitoring mainly comprises three major steps: image segmentation, human body feature extraction and fall detection. In this section, we explain the extraction of the body silhouette that is used in calculating the fall descriptors. The descriptors are discussed in the second part of the section.

2.1 Segmentation and preprocessing

In visual surveillance, the capability of detecting fall events is directly related to wether the extraction of monitored object from a video sequence is performed well. In this study, the human body extraction from the input image sequence is performed using background subtraction technique (Elgammal et al., 2000; Kim et al., 2005). The basic idea behind background subtraction is to use successive frames difference to define stationary pixels corresponding to the background image. Once the background scene is defined, a threshold is then needed to separate pixels belonging to foreground from the background pixels. After segmentation usually some noise regions can be observed. The morphological operators are usually applied to reduce this noise. In this paper, an erosion and dilatation operators using 3 by 3 element are conducted.Figure 1 illustrates an example of the used segmentation method, where the background and the current frames are represented by the two images on the left, respectively, while the two images on the right illustrate results from the background subtraction before and after morphological operators are used, respectively.

Fig. 1. Results of background subtraction algorithm.

2.2 Feature extraction:

An important task in developing a fall detection algorithm consists in feature extraction that are needed to adequately extract the useful features in the data sets. Feature extraction is central to the problem of video-based fall detection and classification. It can be defined as the process by which important discriminative information are extracted from the segmented body. The features have to be invariant to translation and scaling changes. The translation invariance is necessary when the position of human body changes in the image, whereas the scale invariance is needed when the human body dimension changes in the image as the variation of distance between monitored person and camera emplacement. In this study, features are extracted by considering five partial regions of the human body. These areas typically correspond to the body parts in a standing posture, namely: head, arms, and legs as shown in Figure 2; and they are determined by a partitioning based on the body gravity center. A set of ratios which was calculated for each frame is then concatenated to form the feature vector corresponding to the video sequence. Given the total number of pixels making up the body area A, and the number of pixels making up partial areas $A_i, i = 1 \dots 5$, normalized partial areas are given as:

$$R_i = \frac{A_i}{A}. \tag{1}$$

These ratios are computed in order to form the features vector to be used as indicators or descriptors in the fall detection process.

After the feature extraction, the descriptors matrix are used as input data to make decision about the presence or absence of fall. For fall detection purpose, we will investigate the popular data-driven method PCA for performing fall detection. More details about PCA, and how it can be used in anomaly detection are presented next.

3. PCA FOR ANOMALY DETECTION

The purpose of PCA is to model the dependency structure of multivariate data in order to obtain a compact representation of the original data and eliminate insignificant data (MacGregor and Kourti, 1995; Harrou et al., 2015). It can be very helpful when dealing with highly cross-correlated data (MacGregor