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**Survey On Day or Night Activity Recognition From Video Using Fuzzy Clustering
Techniques**

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Abstract

The number of older adults growing dramatically. There is desire to keep older adults healthy, functionally able, and living independently, because this provides a better quality of life, and in part because the aging population will stress Current facilities and resources designed to care for elders. Falls are the most widespread domestic accidents among the elderly people, disabled persons and patients. Their consequences often give rise to impairments to the health and lifestyle of the victims. In many cases, physical after-effects and other injuries are direct consequences of these accidents and result in significant medical costs.

Keywords: Fuzzy clustering techniques.

Introduction

The number of older adults growing dramatically. There is desire to keep older adults healthy, functionally able, and living independently, because this provides a better quality of life, and in part because the aging population will stress Current facilities and resources designed to care for elders. Falls are the most widespread domestic accidents among the elderly people, disabled persons and patients. Their consequences often give rise to impairments to the health and lifestyle of the victims. In many cases, physical after-effects and other injuries are direct consequences of these accidents and result in significant medical costs. Furthermore, it frequently happens that elderly people who have previously experienced a fall, fear a new fall and sink gradually into inactivity and social isolation. Therefore, it is important to detect fall and send out alert to call for help. But if a fallen person is unconscious and unable to call for help it can lead to irreversible maim and even death. Therefore there is a need of autonomous fall detectors that are capable of triggering an alarm automatically without any intervention of the victim and transferring this information to a remote site. So that the fallen person should get immediate medical aid. An approach for activity state recognition implemented on data collected from various sensors standard web cameras under normal illumination, web cameras using infrared lighting, and the Accelerometer Sensor. Sensors such as the Accelerometers ensure that activity segmentation is possible during day time as

well as night. The goal of activity recognition is to identify activities as they occur based on data collected by sensors. There exist a number of approaches to activity recognition that vary depending on the underlying sensor technologies that are used to monitor activities. It is especially useful for activity monitoring of older adults since falls are more prevalent at night than during the day. The project is an application of fuzzy set techniques to a new domain. The techniques described herein is capable of accurately detecting several different activity states related to fall detection and fall risk assessment including sitting, being upright, and being on the floor to ensure that elderly residents get the help they need quickly in case of emergencies and ultimately to help prevent such emergencies.

Literature review

A markerless computer vision technique specifically designed to track natural elements on the human body surface is presented[1]. The method implements the estimate of translation, rotation, and scaling by means of a maximum likelihood approach carried out in the Gauss-Laguerre transform domain. The approach is particularly suitable for human movement analysis in clinical contexts, where kinematics is at present performed by means of marker-based systems. Human motion analysis and gesture recognition are both fields of great interest in image processing and understanding. Stereophotogrammetric systems make it possible to

capture the coordinates of a set of either active or passive markers fixed on those anatomical landmarks whose spatial trajectories are to be measured [2], [3]. By reconstructing the 3-D position of these markers and hypothesizing the relevant underlying human body model, it is possible to estimate joint kinematics. In marker-based systems, accuracy is undisputed: rms errors in the reconstruction of the 3-D position of the markers not higher than 6 mm for commercially available marker-based systems have been reported. This paper incorporates the GLT-based motion estimation method in order to present a novel method for performing marker-less human motion analysis. The algorithm proposed here, based on the expansion of each frame by special circular harmonic functions called GL functions, showed high levels of accuracy, and the natural markers were successfully tracked in all the videos. This allowed studying the task execution for every subject: by estimating the hip and ankle flexion-extension trajectories, the corresponding angular velocities, and the task duration, it is possible to detect and quantify differences in the strategy adopted by young people as compared to the elderly. In this sense, the results encourage introducing the markerless motion capture based on the GLT algorithm as a valid and viable solution for the kinematic analysis of STS tasks.

The Gustafson-Kessel (GK) algorithm [5] is a powerful clustering technique using in a large number of applications in various domains including image processing, classification and system identification. Its main feature is the local adaptation of the distance metric to the shape of the cluster by estimating the cluster covariance matrix and adapting the distance-inducing matrix correspondingly. The standard GK clustering when the number of data samples (in some clusters) is small or when the data within a cluster are (nearly) linearly correlated. In such a case, the cluster covariance matrix becomes singular and cannot be inverted to compute the norm-inducing matrix. In this paper presents a method to overcome this singularity problem by fixing the ratio between the maximal and minimal eigenvalue of the covariance matrix [4]. Fuzzy clustering can also be used to extract fuzzy if-then rules from data. The ability of the GK algorithm to estimate local covariance and to partition data into subsets that can be well fitted with linear sub-models makes it useful for the identification of Takagi-Sugeno (TS) models. The second technique proposed in this paper is useful when the GK algorithm is employed in the extraction of TS rules from data. It reduces the risk of

overfitting when the number of training samples is low relative to the number of clusters. This is achieved by adding a scaled unity matrix to the calculated covariance matrix. The Gustafson-Kessel [1] algorithm is

$$J(\mathbf{Z}; \mathbf{U}, \mathbf{V}, \{\mathbf{A}_i\}) = \sum_{i=1}^K \sum_{k=1}^N (\mu_{ik})^m D_{ik}^2 \mathbf{A}_i$$

based on iterative optimization of an objective functional of the c -means type:

Here, $\mathbf{U} = [\mu_{ik}] \in [0, 1]^{K \times N}$ is a fuzzy partition matrix of the data $\mathbf{Z} \in \mathbb{R}^n \times N$, $\mathbf{V} = [\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_K]$, $\mathbf{v}_i \in \mathbb{R}^n$ is a K -tuple of cluster prototypes and $m \in [1, \infty)$ is a scalar parameter which determines the fuzziness of the resulting clusters. The distance norm $D_{ik} \mathbf{A}_i$ can account for clusters of different geometrical shapes in one data set:

$$D_{ik}^2 \mathbf{A}_i = (\mathbf{z}_k - \mathbf{v}_i)^T \mathbf{A}_i (\mathbf{z}_k - \mathbf{v}_i)$$

When using the GK clustering algorithm to construct Tagaki-Sugeno fuzzy models, a certain degree of overfitting will be experienced for larger numbers of clusters. In such a case, the performance can be improved by further limiting the maximal ratio between the eigenvalues of the covariance matrix or by adding a scaled identity matrix to the covariance matrix. While these latter modifications can improve the performance for small data sets, with a sufficient number of training samples, this restriction in the freedom of the algorithm may have an adverse effect and on the performance.

This paper explores video-based activity monitoring and functional assessment for eldercare [6]. The video data, coupled with intelligent computer vision and learning algorithms, provides a rich and unique set of information that cannot be obtained from other types of sensors. Author propose to develop automated video processing algorithms

- 1) to detect and track human in a home-living environment and
- 2) to extract important ADL statistics and functional assessment data from videos.

They Proposed real-time processing and automated analysis of indoor activity monitoring videos.

1. They developed an accurate and robust silhouette extraction and human tracking algorithm which is able to effectively remove shadow and handle dynamic background changes in an indoor living environment.

2. Author developed an adaptive learning and fuzzy inference system to estimate physical locations and

moving speeds of persons from a single camera view without calibration.

3. Using hierarchical decision tree and dimension reduction methods, They developed an adaptive feature selection and human action recognition scheme to extract important activity statistics and functional assessment data from continuous activity monitoring videos.

4. Author deployed the camera system in a real living environment.



Fig 1. Overview of the proposed framework for automated activity analysis, summarization and visualization

Author construct advanced algorithms for silhouette extraction, human detection and tracking in an indoor living environment. During algorithm development, They focus on two major issues: shadow removal and adaptive background update. To test and evaluate the proposed algorithms and methods for automated activity analysis and summarization in eldercare, They build a large dataset of activity monitoring videos.

Silhouette extraction, namely, segmenting a human body or objects from a background, is the first and enabling step for many high-level vision analysis tasks, such as video surveillance, people tracking and activity recognition. Extracting features to differentiate foreground objects from background is the first step of silhouette extraction. A basic requirement is that features should be invariant under brightness changes. Further, it should be effective in differentiating shadow from background. In this work, Author use two features: brightness distortion and chromaticity distortion. More specifically, we they features in the RGB color space. A key element in automated activity analysis for eldercare is the estimation of the physical location and moving speed of a person. Physical locations of the person in the room provide important contextual information for action recognition. For this purpose develop statistical learning approach for estimating physical location and moving speed from a single fisheye

camera without calibration. Basic idea is when a person appears at the same physical location, his silhouette should look similar, even with lens distortion and object occlusion.

Every year, many older adults are at risk for falling, especially in the dark[7]. Infrared lighting provides a nonintrusive lighting in the dark and research shows a technique of segmenting human activities using fuzzy clustering of image moments even in the dark. Background subtraction techniques using Mixture of Gaussian models with texture features are used on the raw image data to separate the foreground from the background, and the resulting silhouettes are then taken as input to the automatic activity segmentation system. Since researcher goal is to build an automated video surveillance system to continuously monitor elderly persons as they perform their day-to-day activities, they maintain their privacy by using silhouettes instead of raw images .Silhouette extraction is a background change detection technique whose accuracy depends on how well the background is modeled. The background subtraction method implemented in our work uses color and texture features employs shadow removal for greater accuracy. Binary morphological operations are used to fill up holes and remove noise from the extracted silhouettes.

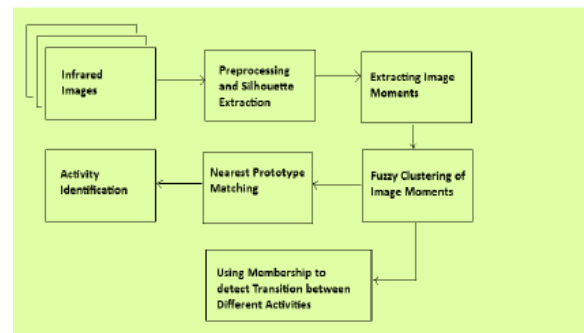


Fig.2 . Block Diagram of Algorithm

After obtaining the silhouettes from the image sequence, the next step in the algorithm is extracting image moments.

The Gustafson Kessel fuzzy clustering technique was implemented on the image moments. The Gustafson Kessel (GK) Algorithm is an extension of the Fuzzy C-Means algorithm in which each cluster has its own unique covariance matrix. This makes the algorithm more robust and more applicable to various data sets which contain ellipsoidal clusters of different orientations and sizes.

The development of an application capable to identify human eating and drinking activity can be

really useful in a smart home environment targeting to extend independent living of older persons in the early stages of dementia[8].

In this paper a novel method aiming at eating and drinking activity recognition is presented. Activities are considered as a sequence of human body poses forming 3D volumes, in which the third dimension refers to time. Fuzzy Vector Quantization is performed to associate the 3D volume representation of an activity video with 3D volume prototypes and Linear Discriminant Analysis is used to map activity representations in a low dimensional discriminant feature space. A system that automatically recognizes eating and drinking activity, using video processing techniques, would greatly contribute to prolonging independent living of older persons aiming at patients in the early stages of dementia. In the preprocessing phase, videos capturing a person during a meal intake are manually segmented to smaller ones depicting elementary activities, e.g., an eating sequence, producing the so-called activity videos. In the case of continuous activity recognition, i.e., recognition in videos containing multiple elementary activities, smaller videos are automatically produced by using a sliding window consisting of N_{tw} video frames, in both training and test phases. Thus, the resulted activity videos are produced by, probably, overlapping video segments. Binary images depicting the image locations that belong to the person's ROIs, i.e., his/her head and hands, in white and the remaining locations in black are obtained by applying a skin color segmentation algorithm at each activity video frame. A Camera placed in front of a person during a meal is used to gather the necessary information. A color segmentation algorithm is used in order to provide a privacy preserving human body representation. Volumetric representation of activities is achieved by concatenating successive binary images representing human body poses. The circular invariance property of the magnitudes of the DFT transform is exploited to provide time invariant activity video representation .

In this paper author present preliminary work to affordably detect sit to stand strategies associated with balance impairment using web cameras [9]. The long term goal is to create systems that can monitor functional movements that are common at home in a way that reflects changes in stability and impairment. Sit to Stand Strategies known to impact the ability to rise from a chair include foot positioning, movement of the torso, and swinging or pushing with the arms against the chair while rising. Detecting an STS strategy with web cameras involves extracting features from input images and relating

them to canonical poses or motions that represent the strategy. In system includes three Logitech web cameras that record at a rate of 30 frames per second and are synchronized by means of a DirectShow filter. Video is encoded in MPEG4 format, at a resolution of 340 x 280 pixels, and is transferred to a laptop via USB. To compute two and three dimensional image features, first extract silhouettes of people from two dimensional views by means of foreground segmentation. From these two dimensional silhouettes, Hu moments are computed, as these are shape descriptors that are robust to changes in scale and translation. To create three dimensional reconstructions, They triangulate silhouette centroids across all camera views. This creates a single three dimensional point corresponding loosely to the position of a tracked individual's torso.

Conclusion

There are various fall detection systems which perform well for the detection, but not suitable for real time applications because of the larger number of sensor nodes attached to human body and uncomfortable wearing condition. The proposed system will be a wearable, portable device mounted on the waist of user, having sensors consisting of accelerometer. The propose fall detection system can be regarded as alternative device to the existing detection approaches, since the device provides the comfortable wearing, is less complex as compared to other devices, fast fall response and will be more accurate and economical.

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