Visual Monitoring System for Elderly People Daily Living Activity Analysis

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***Abstract*— In today modern world, due to the increasing number of older and vulnerable people better and new approaches are needed to support people in their own homes. Especially, intelligent visual monitoring system recognizes the activities of elderly people daily living become more and more important. This paper proposes a new approach for detecting the daily activities of elderly people whether they are deviated from normal behavior. In this context we will focus on building stochastic models of behavior based on types of activity. Models are trained using only normal behavior. Variations from the models are considered as abnormal behaviors and these can be highlighted for subsequent review or intervention. Experimental results are shown by using some real life datasets to illustrate the proposed models.**

***Index Terms*— Visual Monitoring System, Elderly Daily Activities, Abnormal Behavior, Stochastic Models**

I. Introduction

THE population of elderly people is growing dramatically and expected to grow more over the next half century. This trend will lead to the number of people requiring care will grow accordingly. Unless the elderly people receive sufficient care, they will be facing some problems for their independent living. Thus a system permitting elderly to live safely at home is more than needed. Most of health care and medical professional believe that one of the best ways to detect emerging physical and mental health problems, before it becomes critical - particularly for the elderly - is analyzing the human behavior and looking for changes in the activities of daily living. These activities include sleeping, meal preparation, eating, housekeeping, bathing or showering, dressing, using the toilet, doing laundry, and managing medications [1]. As a solution to this issue, we propose an approach which consists of visual monitoring and stochastic modeling of key human postures useful to recognize some interesting activities of elderly. In this paper, we focus on recognizing activities that elderly are able to do (e.g. ability of elderly person to reach and open a kitchen cupboard). The recognition of these interesting activities helps medical experts (gerontologists) to evaluate the degree of frailty of elderly by detecting changes in their behavior patterns. We also focus on detecting critical situations of elderly (e.g. feeling faint, falling down), which can indicate the presence of health disorders (physical and/or mental). The detection of these critical situations can enable early assistance of elderly.

In this paper, we organize as follows. In section 2 some related works are presented followed by the overview of proposed method in section 3.Some experimental results of the proposed method are shown in section 4. Finally, conclusion and future works are described in section 5.

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II. Some Related Works

Visual monitoring system for elderly people daily activity analysis aims to improve the quality of elderly life with the aid of modern technology and prolong the period of independent living in their own home. Due to aging some common problems arise among the elderly people such as memory disorder, action obstacles and etc. [2-3]

Thus, an intelligent visual monitoring system will be needed to install in the living environment of elderly people in order to thoroughly observe the activities and behaviors of elderly people [4-5]. Then, the system will learn the activities and behaviors of elderly people who involved the system. Based on the learned model if unusual behaviors or activities of the user are observed the system will send an alarm signal to the caregiver. Furthermore there will be no sensor to wear on the body or to be activated by the user. In general, the system consists of two sets of functions namely, the basic set and the interactive set. The function of the basic set includes the basic tasks of everyday life such as eating, bathing, walking, toileting and dressing. The interactive set includes the activities that people do in interactive manners such as phone use, watch TV, talk visitors etc. [6-7].

Most of common methods employed for elderly care monitoring system are Markov modeling and Bayesian approaches [8-9]. Here the Bayesian posterior probability was used for choosing the states to merge and for the stopping criterion. Sometimes, a variable-length Markov models can be used to efficient Bayesian to analyze the motion detector data, to learn the behavior of the user.

III. Overview of Proposed Monitoring System

The proposed visual monitoring system is built as a Multi-Layered Markov Model in which there includes five Interactive Layers. The first layer is root layer and the last layer is output layer. The second to fourth layers are

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environment layer, activity layer and objects layer respectively as shown in Fig 1.

First we define a mode as the set of activities performed by the elderly person. In particular, the mode may contain the personal behavior, its interaction with the system and surrounding objects and the degree of personal dependency. These modes will consider the constraints and difficulties which can cause the elderly people obstacles for their daily life. The considered actions are those performed towards the system, such as: Off, On, Alarm, Warning. It is necessary to use an efficient model to recognize the mode of the elderly person.

The majority of previous works were based on the Markov model as a model for the recognition of old people activities focused only on a particular event of eating dinner [9-10].

In the proposed system, each activity has its own environment. For example, “the person cannot prepare a meal in the bedroom”, “the person cannot sleep in the bathroom”, etc. In order to simplify the recognition of activities, we tailor each activity to the location where it is performed. We consider a common home architecture that consists of: Bedroom, Bathroom (including toilets), Kitchen and Living room. In this paper, we propose a Hidden Markov Model to classify the activity of the person by the room of home with essential utilities as described in Table 1.

In order to compute a model we first define the relationship between layers. Each layer contains the elements of the same nature starting from the root Layer (Home). For example, the second layer includes the set of possible places, the third is for the objects of the home and the last layer (layer 4) represents all the actions and movements of the elderly person. Layer 1 is the root environment. Layer 2 is the main environment. All these layers have a direct link between them, for example if the person turn-on the TV, the following action will be most probably- watching TV. Consequently, we cannot pass from layer n to layer n+2. These links allow us to make a complete mode starting with the kind of place where the action is realized by the resident. Concerning the “level 3”each activity can have from 1to n object(s) with n is the number of objects used in this activity. The link between each object in the same “layer 4” is the <and>. Example: the person at home, in the kitchen, preparing meal, use stove and refrigerator.

With the aid of HMM, we are able to detect the abnormal activities by discovering the hidden states.

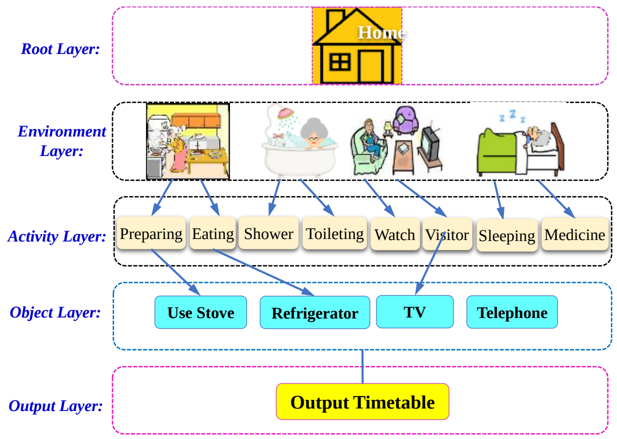

Fig. 1. Overview of the Proposed System.

TABLE I
DESCRIPTION OF HOME FUNCTIONS

Room Type	Activities	Utilities
Kitchen	Preparing meal, Eating, Drinking, Washing dishes	Stove, Refrigerator, Coffee Maker
Bath Room	Taking Shower, Bath, Toileting	Bath tub, Soap Toilet
Living Room	Watching TV, Using Telephone, Meeting with visitor	TV, CD Player, Telephone, Chair Table
Bed Room	Sleeping, Reading, Taking Medicine, Day Dreaming	Bed, Books, Medicine

3.1 Technical Details

Hidden Markov Model

In order to formulate the daily activity of elderly care problem as Hidden Markov Model, we first divide a day into 48 time interval having 30 minutes length of each time interval. Let $S_j(t)$ be the state that the elderly person is in room j (j=1, 2, 3, 4) at time t for t=1, 2, 3,…, 48. By using visual monitoring system we can estimate the following transition probabilities, initial probabilities and emission probabilities.

Transition Probability:

$$p_{ij}(t) = \Pr\{ S_j(t+1) \mid S_i(t)\}$$

Transition Probability Matrix:

$$A(t) = [p_{ij}(t)]$$

Initial Probability Vector:

$$\pi = \{\pi_1, \pi_2, \pi_3, \pi_4\}$$

Emission Probability Matrix:

$$B = [b_i(k)]$$

where

$$b_i(k) = \Pr\{O_t=k \mid S_i(t)\}$$

in which O_t is the observation of the system at time t.

We then establish a Hidden Markov Model $\lambda = (\pi, A, B)$ and employ a forward algorithm to find the state sequence

$$S= \{S_1(t), S_2(t), S_3(t), S_4(t)\}$$

for t = 1,2,…, 48.

From this state sequence we can detect the abnormal behavior of elderly people by observing the time duration at which the person spent at one location more necessary (this can be done by using predefined threshold). For example we consider a piece of three rooms where each room is equipped with a visual monitoring system for presence, motion, etc... The information provided by each subsystem allows to know about the activities and the presence of the person. In our simulation, each room is linked to specific activity. The simulation period is fixed a duration say 5 or six hours. We simulate these activities in a random way. Each mode has a specific set of visual cameras regarding each room. In our

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case, we simulate these modes during 6 hours: from 6:00 to 12:00 A.M. Each room contains a specific mode which contains from one to n activities. Example: at 6:00 A.M. the person wakes up in the bedroom, takes toileting at 6:15 in the bathroom. In the kitchen, elderly prepares his breakfast at 8:00. Afterwards, he washes the dishes then goes to the living room to watch TV at 9: 30. Later on, the elderly has entered the kitchen to prepare his meal at 12:00 then he takes his medication in the bedroom at 12:45.

This example contains three modes: The kitchen mode: preparing breakfast at 8:00; Wash these dishes at 8.30; preparing meal at 11:00. The bedroom mode: wakes up at 6:00; Take medication at 12.45. The living room scenario: watch TV at 9.30.

We then simulate the model to investigate the daily activities of elderly people living independently.

IV. Simulation Results

In order to simulate the current model, it is necessary to describe these parameters (N, A, B, Π) where N is the number of state, A is the transition matrix, B is the emission matrix and Π is the initial matrix. The following matrices A, B and Π are row stochastic, which means that each element is a probability and the elements of each row sum to 1, that is, each row is a probability distribution. In this case, we implement our modes with the following matrices.

Transition matrix: this matrix represents the probabilities of the transition between the states where each state represents a human mode.

A	Mode K	Mode L	Mode B
Mode K	0.15	0.715	0.1
Mode L	0.1	0.8	0.1
Mode B	0. 1	0.11	0.8

Initial matrix: This matrix represents the probabilities of the initial state.

	Mode K	Mode L	Mode B
Π	0.6	0.2	0.2

Emission matrix: contains the emission probabilities, the probability to emit each observation for each state.

	Mode K	Mode L	Mode B
B	0.2	0.6	0.2

By using the synthetic data we estimate the three Modes (Mode L, Mode K, and Mode B) according to the time.

We can perform the estimation of the hidden state" in this context the state is the place/location of the person" for each room in (300 min) using the Mode L (Living-room scenario), K (Kitchen) and B (Bath-room). We obtain the transition matrix as

0.105263	0.561407	0.33333
0.105263	0.561407	0.33333
0.105263	0.561396	0.333341

The state vector after 300 minutes, we get

0.105263	0.561405	0.333332

These results show that the elderly people spent more time in the living room rather than the bed room. More real data will be needed to make accurate results.

V. Conclusion

In this work, we were interested in the events recognition in smart environments for elderly and dependent persons. Our objective was to identify and experiment an efficient recognition model. The simulation results reveal that the proposed model is efficient for activities recognition with an observation error rate that is not very large compared to our hidden states. In the next steps of this work, we will explore the enrichment of our approach by investigating the learning-based systems (such as neural networks with a new learning algorithm) in order to recognize the events accurately.

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