



# **A Methodology for Abnormal Action Detection Based on HHMM Algorithm**

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**ABSTRACT:** Detecting abnormal activities from sensor readings is an important research problem in activity recognition. This paper presents a method for indexing activities of daily living in videos acquired from wearable cameras. It addresses the problematic of analysing the complex multimedia data acquired from wearable devices, which has been recently a growing concern due to the increasing amount of this kind of multimedia data. Our work introduces a video structuring approach that combines automatic motion based segmentation of the video and activity recognition by a hierarchical two-level Hidden Markov Model(HHMM). We define a multimodal description space over visual and audio features, including mid-level features such as motion, location, speech and noise detections. We show their complementarities globally as well as for specific activities. Experiments on real data obtained from the recording of several patients at home show the difficulty of the task and the promising results of the proposed approach. The evaluation metrics need to know the performance of the developed algorithm is Peak Signal to Noise Ratio, Structural Similarity Index Map.

**KEYWORDS:** Abnormal action, Hierarchical Hidden Markov Model, Action recognition, Peak Signal to Noise Ratio, Structural Similarity Index Map.

## **I. INTRODUCTION**

Action acknowledgement plans to perceive the activities and objectives of one or more specialists from a progression of perceptions on the specialist's activities and the natural conditions .Since the 1980's,this exploration field has caught the consideration of a few software engineering groups because of its quality in giving customized support for a wide range of uses and its association with a wide range of fields of concentrate, for example ,medication, human –PC cooperation, or humanism.

To comprehend movement acknowledgment better, consider the accompanying situation. An elderly man awakens at day break in his little studio loft, where he stays alone. He lights the stove to make a pot of tea, switches on the toaster broiler, and takes some bread and jam from the organizer. In the wake of taking his morning pharmaceutical, a PC created voice tenderly reminds him to kill the toaster. Soon thereafter, his little girl gets to a secure site where she filters a registration, which was made by a sensor system in her dad's condo. She finds that her dad is eating regularly, taking his solution on calendar, and proceeding to deal with his day by day life all alone that data comforts her psyche. A wide range of utilizations have been considered by analysts in movement acknowledgment; cases incorporate helping the wiped out and debilitated. Consequently observing human exercises, home-based restoration can be accommodated individuals experiencing traumatic mind wounds. One can discover applications going from security-related applications and logistics backing to area based administrations. Because of its numerous faceted nature, distinctive fields may allude to action acknowledgment as arrangement acknowledgment, objective acknowledgment, goal acknowledgment, conduct acknowledgment, area estimation and location based administrations.

The rest of this paper is organized as follows. Section II first reviews existing method. Our proposed method is described in Section III. Then algorithm in Section IV and experimental results are reported in Section V to demonstrate the superior performance of our framework. Finally, conclusions are presented in Section VI.

# International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2016

## II. RELATED WORK

Human identification at a distance has recently gained interest from computer vision researchers. Human recognition aims essentially to address this problem by identifying people based on the way they walk. A simple but efficient human recognition algorithm using silhouette analysis is proposed. For each image sequence, a background subtraction algorithm and a simple correspondence procedure are first used to segment and track the moving silhouettes of a walking figure. To track the behaviour of silhouette between two different frames, we need to know the possible cases that may occur. They could be the different distances between the light and the object, which includes the following situations: When silhouette is larger than the previous frame (small distance). When silhouette is smaller than the previous frame (large distance). When silhouette changes shape with change in position (similar distance). In this case it's easy to find the silhouette edge from previous once by picking an edge based on 1) either of the two adjacent faces if visible with one face visible to the light position. 2) If both are visible and one is visible to the light, silhouette edge further away from light is to be checked and 3) if both are invisible also to the light, silhouette edge nearest to light is to be checked.

Several algorithms can be followed to choose the path from one edge to another in order to find the silhouette edge. We use the left to right approach to walk on the objects models faces to find the silhouette edge. Since the second vertex of the last edge would always be same to the first edge of the first vertex of the silhouette (a kind of circle), it's easy to track a silhouette and its behaviour.

## III. PROPOSED ALGORITHM

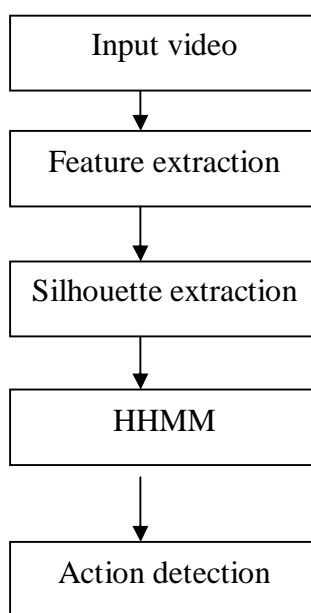


Fig.1: Flow Diagram of Proposed Method

### A. HIERARCHICAL HIDDEN MARKOV MODEL IN DETECTING ACTIVITIES

In the Hierarchical Hidden Markov Model each state is considered to be its own probabilistic model i.e. it will activate one of the states of the underlying HHMM, which in turn may activate its underlying HHMM and so on until a specific state, called a production state is activated that emits observation symbols. The states that do not directly emit observation symbols are called internal states. The activation of a state in an HHMM under an internal state is known as vertical transition. After the completion of vertical transition, horizontal transition occurs to a state within the same

# International Journal of Innovative Research in Computer and Communication Engineering

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level..If the horizontal transition leads to a terminating state control is returned to the state in the HHMM, higher up in the hierarchy, that produced the last vertical transition. To simplify notation we restrict our analysis to HHMMs with a full underlying tree structure, i.e., all the leaves are at the same distance from the root state.

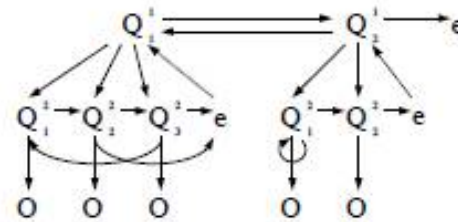


Fig.2: A two-level HHMM with observations at the bottom.

Black edges denote vertical and horizontal transition between states and observations  $O$ . Dashed edges denote returns from the end state of each level  $e$  to the level's parent state  $Q_i^d$  ( $i$  is the state index,  $d$  is the hierarchy level)

To construct a two-level HHMM which considers parts of motion as separate sub models. The top HHMM level corresponds to the main actions in the motion data, and at the bottom the initial data sequence is divided into sub sequences according to the actions they represent. The choice of the number of levels is natural: every data sequence has at least a single pattern (subsequence), while having more levels could be unnecessary for many applications as well as being computationally expensive.

A full HHMM is defined as a 3-tuple

$$H = \langle \lambda, \zeta, \Sigma \rangle$$

Here  $\lambda$  is a set of parameters,  $\zeta$  is the topological structure of the model, and  $\Sigma$  is an observation alphabet. The set of parameters  $\lambda$  consists of a horizontal transition matrix  $A$ , mapping the transition probability between child nodes of the same parent; an observation probability distribution  $B$  and a vertical transition vector  $\prod$  that assigns the transition probability from a hidden node to its child nodes:

$$\lambda = \langle A, B, \prod \rangle$$

$A^{qd} = a_{ij}^{qd}$  where  $a_{ij}^{qd} = P(q_j^{d+1} / q_i^{d+1})$  is the probability of making a horizontal transition from  $i^{th}$  state to  $j^{th}$  state in which both are substates of  $q^d$ .

$\prod^{qd} = \{\pi^{qd}(q_i^{d+1})\} = \{P(q_i^{d+1} / q^d)\}$  is the initial distribution vector over the substates of  $q_i^{d+1}$  in which the probability of state  $q^d$  will initially active the state  $q_i^{d+1}$ .

$B^{qD} = \{b^{qD}(k)\}$  where  $b^{qD}(K) = P(\sigma_k / q^D)$  is the probability that the production state  $q^D$  will output the symbol  $\sigma_k \in \Sigma$ .

The entire set of parameters is denoted by

$$\lambda = \{ \lambda^{qd} \mid d \in \{1, 2, \dots, D\} \} \\ = \{ \{ A^{qd} \} \mid d \in \{1, 2, \dots, D-1\}, \{ \prod^{qd} \} \mid d \in \{1, 2, \dots, D-1\}, \{ B^{qD} \} \}$$

The topology  $\zeta$  specifies the number of levels, the state space at each level, and the parent-children relationship between levels. The states include "production states" that emit observations and "abstract states" which are hidden states. The observation alphabet  $\Sigma$  consists of all possible observation finite strings.

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(An ISO 3297: 2007 Certified Organization)

Vol. 4, Issue 11, November 2016

In this paper, the objective is the indexing of the instrumental activities in audiovisual data recorded with a camera worn by the patient using the paradigm of first-person sensing. Aim of the proposed algorithm is to present the methods and algorithms developed for the multi-modal analysis of audio-visual data captured from such a wearable device. Key contributions include: - a hierarchical two level Hidden Markov Model (HMM) aimed at the detection of activities of daily living, which provides the fusion of multi-modal visual and audio features. These include both low-level descriptors and mid-level features, some of which have been designed for the type of data considered; we show the complementarities of the chosen features globally, and show how specific activities can gain from this; - a new method for partitioning the data stream into segments, which is designed for continuous video sequences such as those captured by a wearable camera; - experiments and evaluation on real-life data acquired on both volunteers and patients in the context of the analysis of their activities of daily living. The paper is organized as follows: we give the motivation for our application of audiovisual life logging for the analysis of activities of daily living and describe the architecture of the proposed approach. We provide a detailed explanation of the hierarchical HMM. In this method for partitioning the videos and strategy for the extraction of meaningful multimodal features which feed the HMM as observations.

## B. ACTIVITY RECOGNITION IN MULTIMEDIA DATA.

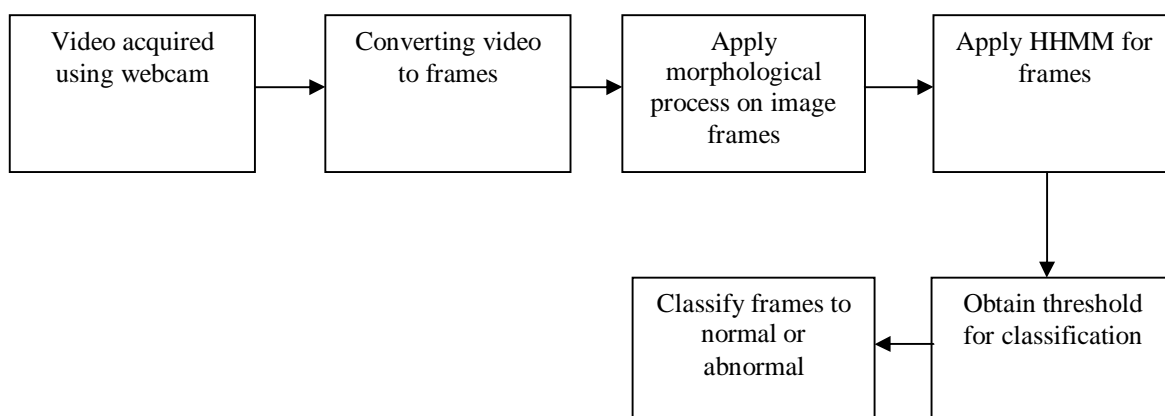


Fig.3. Block Diagram of HHMM Activities Recognition

## IV. ALGORITHM

- Step 1: Read video from the web camera and convert video into frames.
- Step 2: Using background subtraction algorithm obtain the silhouette of the frames.
- Step 3: Apply the HHMM algorithm and calculate  $A, B, []$ .
- Step 4: Create the gray level co-occurrence matrix from the image using  $glcms = graycomatrix(s);$  where  $s=rgb2gray(I)$
- Step 5: Compute the statistics from glcms i.e., Contrast, Correlation, Energy, Homogeneity.
- Step 6: Obtain threshold for classification of frames.
- Step 7: Finally based on threshold classify frames to normal or abnormal.

## V. RESULTS

Here first the input video from the web camera is taken and performed feature extraction to obtain silhouettes for the human action. Then HHMM algorithm is used to detect abnormal action.

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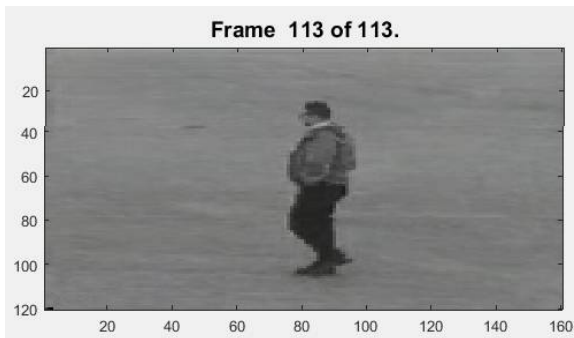


Fig. 4: video into frames

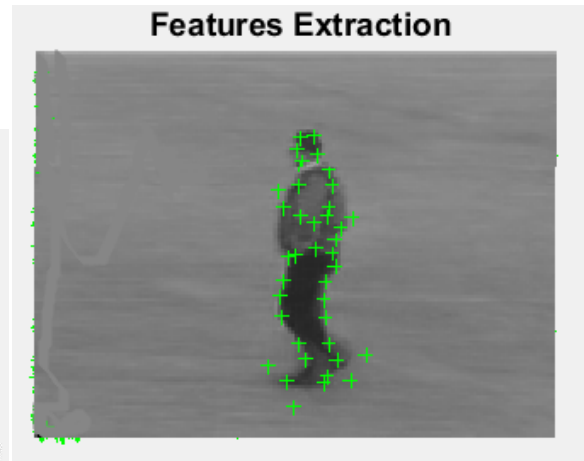


Fig 5: feature extraction

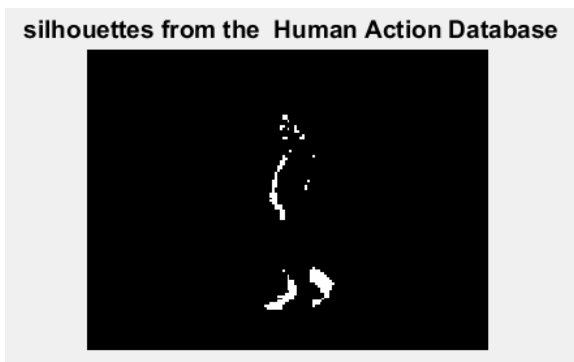


Fig. 6: Silhouette extraction



Fig 7: Action detection.

Comparison Table:

	PSNR	SSIM
<b>Proposed method</b>	<b>50.2054</b>	<b>0.9980</b>
<b>Existing method</b>	<b>37.3787</b>	<b>0.9687</b>

Table1: comparison of proposed and existing methods

## VI. CONCLUSION AND FUTURE WORK

In this paper, the proposed method is an efficient way to abnormal action recognition using HHMM algorithm. These videos are complex, with strong and irregular motion and lighting changes, the presence of activities of interest in the recordings is rare. A Hierarchical two level HMM was proposed to model both the semantic activities from the taxonomy defined by medical doctors and non-semantic intermediate states. Our method is simple and a new concept of camera “viewpoint” and proposed a temporal segmentation of the video thanks to the analysis of the apparent motion. The proposed model was tested on the unique-in-the-world video corpus acquired with healthy volunteers and patients in an “ecological” environment, i.e. at their homes. The taxonomy of activities was defined by medical



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researchers and the proposed framework was tested with cross-validation to recognize. Even though our system brings good results for action detection, it has to compromise some quality of image which can be resolved in future.

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