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Unsupervised discovery of human activities from long-time videos

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Abstract

In this paper, we propose a complete framework based on a Hierarchical Activity Models (HAMs) to understand and recognise Activities of Daily Living (ADL) in unstructured scenes. At each particular time of a long-time video, the framework extracts a set of space-time trajectory features describing the global position of an observed person

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and the motion of his/her body parts. Human motion information is gathered in a new feature that we call Perceptual Feature Chunks (PFC). The set of PFC is used to learn, in an unsupervised way, particular regions of the scene (topology) where the important activities occur. Using topologies and PFCs, we break the video into a set of small events (*Primitive Events*) that have a semantic meaning. The sequences of *Primitive Events* and topologies are used to construct hierarchical models for activities. The proposed approach has been experimented in the medical field application to monitor patients suffering from Alzheimer and dementia. We have compared our approach with our previous study and a rule-based approach. Experimental results show that the framework achieves better performance than existing works and has a potential to be used as a monitoring tool in medical field applications.

1 Introduction

Nowadays, there are many applications (such as surveillance, human-computer interaction, etc.) that require an efficient and accurate analysis of human activities using video input. For example, in the medical field, the behaviour

5 of patients (e.g. suffering from dementia or Alzheimer disease) needs to be
6 studied on a long-period of time (days and weeks) in order to help medical
7 staff (doctors, carers and nurses) to understand the difficulties of patients
8 and propose solutions that can ameliorate their daily living conditions [3].

9

10 Modelling and recognising activities is a rising field in computer vision and
11 machine learning. Recent approaches [10, 26] address the problem of detect-
12 ing complex daily activities using egocentric wearable cameras which enable
13 to have a close view and see the objects in their natural positions. However,
14 a wearable camera can be very intrusive for the user, especially for people
15 suffering from dementia. Visual information can also be obtained with fixed
16 cameras. The majority of work in activity recognition using fixed cameras
17 addresses short-term actions (i.e. few seconds) in acted footages of posture-
18 defined classes such as “punching” [29, 13]. In order to recognise human
19 activities, scenes need to be analysed from a sequence of frames (low-level
20 task of computer vision) and interpreted (high-level task). The inability of
21 connecting these two levels (high-level and low-level tasks) is called semantic
22 gap problem [31] and its reduction is still a challenging task.

23

24 In this paper, we propose a new approach to reduce this gap by constructing,
25 in an unsupervised manner, an intermediate layer between low-level informa-
26 tion (tracked objects from video) and high-level interpretation of activity (e.g
27 cooking, eating, sitting). Our method is a novel approach allowing the detec-
28 tion of complex activities with long-duration in an unstructured scene. We
29 have developed a complete vision-based framework that enables to model,
30 discover and recognise activities online while monitoring a patient. Two
31 main contributions of this work are as follows:

- 32 1. An intermediate representation of features (the *Primitive Events*) com-
33 posed of basic activities which structures the person motion with re-
34 spect to a spatial topology.
- 35 2. A hierarchical activity model, that can categorize complex activities
36 using increasing granularity levels of the spatio-temporal structure of
37 basic activities.

38 In our previous study [28], by using the same tracking and topology learning
39 procedures, we have proposed an unsupervised method that models activi-
40 ties only based on frequency histograms of two features: i) type of primitive
41 events and ii) the direction of local dynamics. One drawback of this method

42 is that the models are characterized without considering the hierarchical links
43 between primitive events. In order to cope with this drawback, in this paper,
44 we have proposed a new activity model, called hierarchical activity models
45 (HAMs) that take into account the hierarchical structure of primitive events.
46 In addition, we have extended the evaluation by using a dataset that includes
47 non-guided activities of daily living (ADL) and demonstrated that, by using
48 HAM, we achieve better performance than existing works.

49

50 We start in Section 2 by presenting the related work and previous approaches
51 in the field of activity recognition. An overview of the proposed activity dis-
52 covery framework is presented in Section 3 . In Section 4, we describe the
53 low-level video processing and the primitive events. We introduce the process
54 of building the hierarchical activity model in Section 5. Experimental results
55 are discussed in Section 6 and the conclusion is presented in Section 7.

56 **2 Related work**

57 Activity analysis and recognition using video is a fast-growing field based
58 on different methods and techniques. The goal of activity recognition is

59 analysing human activities from an unknown video based on the movements
60 of the person. In general, videos are captured either by a fixed camera
61 [13, 12, 35] or by a wearable camera [25, 32, 11, 10, 26]. A complete overview
62 of the previous methods on human activity recognition is proposed in [2]
63 in which the authors emphasize the importance of high-level activity under-
64 standing for several important applications, namely those related to ADL.

65

66 A major group of previous work in activity recognition includes knowledge
67 and logic-based approaches [23, 16]. For example, authors in [35] proposed
68 a monitoring system for analysis and recognition of human activities. It in-
69 cludes detecting, tracking people and recognising some pre-defined activities
70 using posture information. Three sources of knowledge were exploited: the
71 model of activities, the 3D model of the observed scene, and the 3D model
72 of the mobile object present in the observed scene. In [7], a knowledge-based
73 method is proposed for older people monitoring. Events are modelled as a
74 function of human body context (e.g., sitting, standing, walking), that is
75 obtained from images, and the environment context, which is obtained from
76 accelerometers attached to objects of daily living (e.g., TV remote control or
77 doors use). A rule-based reasoning engine is used for processing, analysing

78 both context types and detect events that fit in rules. While logic-based
79 approach is a natural way of incorporating domain knowledge, for every
80 deployment it requires an extensive enumeration by a domain expert. In
81 addition, there are some methods that utilise Markov logic networks (MLN)
82 to model events using first-order logic in a Markov network [18, 8]. In [18],
83 they represent each target activity as weighted and undirected trees, starting
84 from primitive actions at the bottom to activities at the top. In [8], an MLN
85 is constructed to recognise ADL in a smarthome using non-visual and non-
86 wearable sensors. To overcome the noisy and unreliable observations coming
87 from the sensors, they build logical models can be checked by human and
88 linked to domain knowledge.

89

90 Recently, in order to understand long-term activities a particular attention
91 has been given to trajectory-based approaches that utilize the object tra-
92 jectory information over time. In general, these approaches can be classified
93 into supervised and unsupervised methods. Using a labelled training dataset,
94 supervised methods [15, 20] can build very precise activity models. However,
95 they require large manually labelled training datasets. Also, Hidden Markov
96 Models (HMMs) are applied for the recognition of daily activities [9, 14].

97 [9] introduces the Switching Hidden Semi-Markov Model (S-HSMM), a two-
98 layered extension of the hidden semi-Markov model (HSMM) for modelling
99 low-level and high-level temporal structures of activities. They show that the
100 proposed S-HSMM performs better than the HSMMs and the HMMs in the
101 recognition of frequent and infrequent activities. A recent trajectory-based
102 approach for human activity recognition [14] combines hierarchical Dirichlet
103 process and HMM to address some limitations of HMM, especially in pre-
104 dicting the number of human motion states in videos. But it requires a lot
105 of computation to obtain the number of motion states. The HMM-based
106 approaches tries to recognise activities by modelling the time-series func-
107 tion of events and learning the parameters of the function using supervised
108 learning techniques. However, recognising complex events, such as “prepar-
109 ing meal”, using time sequence is very difficult since the sequential pattern
110 is person-dependent. The unsupervised methods include works such as [17]
111 in which authors learn motion patterns in traffic surveillance videos by us-
112 ing a two-layered trajectory clustering in space and time via fuzzy k-means
113 algorithm. This idea has been extended in [24] and a three-layered cluster-
114 ing is performed on trajectories in order to learn the variations in spatial
115 routes, time duration and speed. Then, the spatio-temporal dynamics of

116 each cluster is encoded by training HMMs using the most representative ex-
117 amples of clusters. Other methods [4, 6] use dynamic programming based
118 approaches to classify activities. These methods are only effective when
119 time ordering constraints hold. The approach in [27] uses HMM to repre-
120 sent trajectory paths by clustering and captures spatio-temporal patterns in
121 trajectory paths. Clustering is based on finding the number of clusters by
122 checking how well eigenvectors of the trajectory correlation matrix span the
123 subspace. This approach allows high-level analysis of activities for detecting
124 abnormalities in traffic videos. However, since ADL are more complex than
125 traffic dynamics, using only trajectories are not sufficient to capture spatio-
126 temporal modalities of ADL and make distinction between activities (e.g.
127 there will be no difference between “standing next to table“ and ”eating at
128 the table“).

129

130 In the literature, there are some methods that use hierarchical models for
131 activity recognition [19, 1, 34]. The described system in [34], extracts fea-
132 tures from wearable sensor data and use a two-layered Bayesian network to
133 model the relation between sub-activities and activities. The sub-activities
134 and conditional probabilities are learned from data but the activities are

135 manually specified. A method that uses passive sensors in smart home en-
136 vironment and a two-layered HMM to model relation between sub-activities
137 and activities is proposed in [19]. Similarly, the system learns sub-activities
138 from data by clustering. For high-level activities, a HMM is trained using
139 manually labelled data. In [1], using the trajectories extracted from a fixed
140 camera, a human behavioural analysis system is proposed. Using time delay
141 neural networks, first, trajectories are classified into four groups: walking,
142 running,loitering and stopping. Then, a rule-based fuzzy system is used to
143 infer macro and group behaviours. The disadvantages of this system is that
144 training is required for neural networks and the fuzzy system requires specific
145 rules to recognise activities, which is not an easy task for complex activities.
146 On the contrary, in our method, without the need of manually annotated
147 ground truth, we automatically learn the hierarchical relations between ac-
148 tivities and sub-activities in an unsupervised way.

149

150 The next section gives an overview of the proposed approach in this paper.

151 **3 Overview of the proposed Activity Discov-** 152 **ery framework**

153 The complete framework that we proposed in this paper can recognise long-
154 term activities (hours) in an unsupervised manner and can be used in un-
155 structured scenes. In order to build a hierarchical activity model that char-
156 acterizes a complex activity, it uses contextual information to create auto-
157 matically an intermediate structure of a basic activity. This is performed
158 by following steps: (i) long-term videos are processed in order to obtain
159 important information (features) about an observed person (i.e. global po-
160 sitions and the motion of his/her body parts), (ii) features are used to learn
161 the multi-resolution levels of the scene regions (topology), (iii) features and
162 scene regions are combined together to build primitive events which repre-
163 sent a primitive state transitions within regions, (iv) based on the primitive
164 events, activities are discovered and the model of an activity is built, (v) the
165 recognition is performed by comparing similarity between models of activity.

166 **4 Low-level video processing and primitive** 167 **events**

168 **4.1 Low-level video processing**

169 Our low-level processing is based on two phases: extracting Perceptual Fea-
170 ture Chunks and learning Topologies.

171 **4.1.1 Perceptual Feature Chunks**

172 We define the Perceptual Feature Chunks (PFCs) as a set of particular infor-
173 mation (i.e. global and local dynamics) associated to human motion in the
174 video. This information is obtained after decomposing the video into short
175 sequences of images (i.e. video chunks) based on the significant changes of
176 human motion (e.g. speed).

177

178 The position of a person, is estimated using a set of tracklets which is com-
179 puted for each video chunk by tracking particular corner points. First, 500
180 corner points [30] are randomly initialized and tracked over time using KLT
181 [5]. Second, we compute 4 clusters (k-means) of the points with respect to
182 their speed and position, representing static, slow, medium and fast motion.

183 Finally, we compute the global position p_t of the person at time t , by averag-
184 ing the centroids of the 3 point clusters (i.e. slow, medium and fast motion).

185

186 Due to noise in images, p_t can be unreliable. Therefore, we obtain a smoothed
187 global position \tilde{p}_t by applying a Kalman filter K_1 to p_t in combination with
188 the last n_s smoothed positions:

$$\tilde{p}_t = \frac{1}{n_s + 1} \left(p_t + \sum_{i=0}^{n_s} K_1(\tilde{p}_{t-i}) \right) \quad (1)$$

189 The sequence of $\{\tilde{p}_t\}$ represents the global trajectory which is represented in
190 Figure 1-(a) by green points.

191

192 We compute the speed of the person s_t at time t as the difference of the
193 position of the person at time t and $t - 1$. Similarly, we compute a smoothed
194 speed, \tilde{s}_t , by applying a Kalman filter K_2 to s_t , in combination with the last
195 n_s smoothed speeds:

$$\tilde{s}_t = \frac{1}{n_s + 1} \left(s_t + \sum_{i=0}^{n_s} K_2(\tilde{s}_{t-i}) \right) \quad (2)$$

196 Finally, the video is decomposed into video chunks by comparing \tilde{s}_t with a
197 threshold.

198

199 Consequently, each video chunk is associated with a PFC that includes fol-
200 lowing attributes : $Departure_{PFC}$, $Arrival_{PFC}$ which are two Gaussian dis-
201 tributions characterizing the position of the person at the beginning and the
202 end of the video chunk. The mean and standard deviation (μ, σ) of the po-
203 sition distributions are computed using the first (or last) n_g points of the
204 global trajectory. $StartFrame_{PFC}$, $EndFrame_{PFC}$ represent the first and
205 last frame number of the video chunk, respectively. $PixelTracklets_{PFC}$ are
206 the pixel-based tracklets used to calculate the global trajectory of the person.
207 An example of $PixelTracklets_{PFC}$ (pink to purple) of a person moving from
208 the armchair to the kitchen is represented in Figure 1-(a). An illustration of
209 the PFC attributes are presented in Figure 1-(b). The feature chunks enable
210 to collect the necessary information for activity understanding and to avoid
211 expensive computational time, especially for long-term activities. The repre-
212 sentation contains minimal but important information about the activity in
213 the scene. For instance, we can store the trajectory information of a 4-hour
214 video in less than 14Kb of memory.

215 4.1.2 The Topology

216 When a tracked person performs activities, he/she interacts with many ob-
217 jects that can be represented by fixed regions (e.g. the person interacts with
218 the kitchen to prepare meal). We name each set of scene regions a topology
219 (or contextual information) and learn each topology by clustering trajectory
220 points ($\{\tilde{p}_t\}$).

221

222 To learn a topology, we use the PFCs associated to one or several peo-
223 ple performing activities in the same scene at various time. From this set
224 of sequences, we extract a set of points, that we call $Points_{Seq}$, using the
225 $Departure_{PFC}$ and $Arrival_{PFC}$ of all videos.

$$Points_{Seq} = \{Departure_{PFC}(\mu)\} \cup \{Arrival_{PFC}(\mu)\} \quad (3)$$

226 We perform k-means clustering [22] over $Points_{Seq}$. The number of clusters
227 represents the level of granularity of the topology, where lower numbers im-
228 ply smaller number of regions that are wider. Each cluster defines a *Scene*
229 *Region* (SR). We denote a topology at level l associated with k clusters as
230 $T_l = \{SR_0^l, \dots, SR_{k-1}^l\}$.

231

232 We represent a *scene model* as a vector of topologies of different resolution
233 levels: $\{T_l\}$. We build this scene model by calculating 3 levels of topolo-
234 gies that correspond to 5, 10 and 15 clusters. Figure 2 describes the scene
235 model obtained by clustering extracted points in the HOMECARE dataset
236 (described in Section 6), corresponding to high, medium and low-level activ-
237 ities.

238 4.2 Primitive Events

239 We propose an intermediate layer called *Primitive Events* that enable to
240 link gradually the extracted features from images (low-level information) to
241 the semantic interpretation of the scene (high-level information).

242

243 *Primitive Events* are the events characterizing Perceptual Feature Chunks
244 (section 4.1.1) over a single topology (section 4.1.2). For each person, a se-
245 quence of *Primitive Events* is built using the sequence of PFCs and a topol-
246 ogy T_l . In practice, we build 3 sequences of *Primitive Events* (for $l = 1, 2$
247 and 3) for a single video.

248

249 *Primitive Events* has 2 attributes, called $Transition_{PE}$ and $LocalDynamics_{PE}$,

250 that contain extracted features and their semantic interpretation.

251 **4.2.1 The $Transition_{PE}$**

252 It describes the movement of a person over the scene by extracting the transi-
253 tion information performed between learned scene regions SR_i^l at one level, l .

254

255 The $Transition_{PE}$ is represented as a directed region pair:

$$Transition_{PE} = (StartRegion \rightarrow EndRegion) \quad (4)$$

256 where $StartRegion$ and $EndRegion$ are the labels of the nearest SR_i^l (i^{th} scene
257 region from T_l) to the $Departure_{PFC}(\mu)$ and $Arrival_{PFC}(\mu)$ positions.

258 **4.2.2 The $LocalDynamics_{PE}$**

259 The $Transition_{PE}$ can only describe the global motion of the person while
260 he/she performs an activity over the scene (moving from one region to an-
261 other one or staying in a region). To be able to model finer activities (low-
262 level activities), we compute the $LocalDynamics_{PE}$ attribute that contains
263 finer information (point tracklets) on the movement of the human body parts
264 (hands, arms, torso, etc).

265

266 The $LocalDynamics_{PE}$ are obtained by clustering the $PixelTracklets_{PFC}$
 267 (section 4.1.1). For clustering, we use the mean-shift algorithm [33]. In the
 268 literature, the methods for tuning the bandwidth of the mean-shift algorithm
 269 are not appropriate to compute a finer description of the local motion. Thus,
 270 we adapt the mean-shift bandwidth automatically as a function of the global
 271 position of the person:

$$h = ||Departure_{PFC}(\mu) - Arrival_{PFC}(\mu)|| \quad (5)$$

272 where h is the bandwidth window. Figure 3 illustrates five examples of the
 273 computed $LocalDynamics$ (green) from the clustering of the $PixelTracklets_{PFC}$
 274 (pink) associated to the following movements: arms up, arms down, join
 275 hands, bend down and stretch up. It can be seen in the figure how local dy-
 276 namics (green tracklets) can capture five activities while the person remains
 277 at the same location.

278 5 Building the Hierarchical Activity Model

279 5.1 The process of Activity Discovery

280 The sequences of $Primitive Events$ are very informative about the activity
 281 occurring in the video. However, a $Primitive Event$ can only describe a

282 snapshot of the person motion. In order to provide more meaning, a better
 283 representation of the discovered activity is needed.

284

285 If a person stays in a region for a certain amount of time, we need to fuse the
 286 sequences of *Primitive Events* to obtain one global activity corresponding
 287 to all the time he/she stayed in the region. Another kind of activity occurs
 288 when the person moves from one region to another. Therefore, we consider
 289 two patterns, *Change* and *Stay*, to describe the two types of activity:

- 290 • The *Stay* pattern characterizes an activity occurring within a single
 291 topology region like "at.region.P", and it is defined as a maximal sub-
 292 sequence of *Primitive Events* with the same *Transition_{PE}*:

$$Stay_{P-P} = (P \rightarrow P)^+ \quad (6)$$

- 293 • The *Change* pattern describes the transition of the person between re-
 294 gions like "changing.from.P.to.Q" which is composed of a single *Primitive Event*:

$$Change_{P-Q} = (P \rightarrow Q), P \neq Q \quad (7)$$

295 We define a discovered activity (DA) at a level l as an extracted *Stay_{P-P}* or
 296 *Change_{P-Q}* pattern:

$$DA_{P-Q}^l = Stay_{P-P} | Change_{P-Q} \quad (8)$$

297 The process of activity discovery is performed over the three granularity lev-
298 els ($l = 1, 2, 3$) by using the three sequences of *Primitive Events*. Therefore,
299 based on the hierarchy of the scene regions, the discovered activities are also
300 classified to coarse, medium and fine and each of them is a sub-activity of an
301 activity at a coarser resolution.

302

303 In the following sections, we replace $P - Q$ and $P - P$ by the index s that
304 represents the semantic of an activity. Each activity are mapped to a colour
305 on the graphical interface to categorize the activities in the video. Figure 4
306 shows the coloured segments representing the discovered activities at three
307 levels of resolution. Same colours correspond to the same activity at each
308 resolution level.

309 **5.2 The Hierarchical Activity Model**

310 **5.2.1 Definition of the model**

311 We represent the model of an activity as a tree of nodes that is obtained
312 by merging the set of $\{DA_s^{l=1,2,3}\}$ (s is the semantics of the activity) and
313 has a hierarchical structure based on the three levels of granularity (i.e.
314 $\{N^{l=1}, \{N_i^{l=2}\}_{1 \leq i \leq n}, \{N_j^{l=3}\}_{1 \leq j \leq m}\}$). The tree of nodes represents how dif-

315 ferent activities and sub-activities are connected to each other thanks to a
316 set of *attributes* and *sub-attributes* obtained from the properties such as
317 type, duration, etc. In other words, a node N is characterized by *attributes*
318 and *sub-attributes*:

- 319 • The *attributes* is a set of parameters over the DAs at the current level
320 l that characterizes the node N^l .
- 321 • The *sub-attributes* constitutes the set of parameters that characterizes
322 the attributes of the sub-nodes N_i^{l+1} , where i is the index of the child
323 node of N^l .

324 5.2.2 Learning phase of the model

325 For a selected instances of the same discovered activities DA_s^l (e.g. $s =$ “cook-
326 ing”), we learn the model of activity by constructing a tree of nodes where
327 each node of level l is built from the set of discovered activities that are at the
328 same resolution level l , $\{DA_{s_1}^l, DA_{s_2}^l, \dots, DA_{s_n}^l\}$ where s_1, s_2, \dots, s_n are parts
329 of s (i.e. sub-activities of cooking). An example of the constructing pro-
330 cess of a tree of nodes from three sequences of discovered activities classified
331 from the coarser to the finer one is illustrated in Figure 5-(a). We construct
332 an independent model for each type of discovered activity. In the following

333 subsections, we describe the parameters of *attributes* and *sub – attributes*.

334 **The attribute of a node** For a node N^l , we define 3 attributes to describe
335 temporal and spatial properties of a node:

336 • *Type*: it is adopted from the DAs composing a node. For a node N ,

337
$$type_N = type_{DA_s}$$

338 • *Instances*: the amount of training instance of activities composing a
339 node.

340 • *Duration*: a Gaussian distribution $N(\mu_d, \sigma_d^2)$ describing the temporal
341 duration of the training instances.

342 • *Histogram of Local Dynamics $H(\theta)$* : is a histogram that charac-
343 terizes the length and the angle of local motion. As it is presented in
344 Figure 5-(b), the length is the magnitude of the local motion vector
345 and the angle is orientation of the vector with respect to x-axis, which
346 is discretised into 8 bins.

347 **The sub-attribute of a node** The sub-attributes enable us to get infor-
348 mation from the child nodes. To compute the sub-attributes of a node, we use
349 the attributes of its child nodes. For a node N^l , we define two sub-attributes

350 named $mixture_{sub-activity}$ and $timelapse_{sub-activity}$ which aim at describing
 351 two properties of the child nodes N_i^{l+1} of N^l :

352 1. $mixture_{sub-activity}$: Describes the amount of time a child node with the
 353 same $Type$ appears. It is represented as a mixture of Gaussians (MOG)
 354 of $(\theta_{type}^{mixture})$ with the following parameters:

- 355 • K , is the total number of components (Gaussians) and equal to
 356 the number of unique $Types$
- 357 • O , is the total number of discovered activities at level l (DA^l).
- 358 • $w_{q=1\dots K}$, is the prior probability of the component q . It is equiv-
 359 alent to the weight of each Gaussian in the MOG. It is computed
 360 based on the number of appearances of the nodes with the same
 361 $Type$:

$$w_q = \frac{\sum_{p=1}^O \delta(Type_{N_p^{l+1}}, Type)}{O} \quad (9)$$

362 Then, $\theta_{type}^{mixture} = \sum_{q=1}^K w_q * N(\mu_q, \sigma_q)$ where μ_q is calculated by the
 363 training instances of all child nodes with the same $Type$:

$$\mu_q = \frac{\sum_{p=1}^O Instances_{N_p^{l+1}} * \delta(Type_{N_p^{l+1}}, Type)}{\sum_{p=1}^O \delta(Type_{N_p^{l+1}}, Type)} \quad (10)$$

364 2. $timelapse_{sub-activity}$: Represents the temporal distribution of child nodes.
 365 For an activity, it describes the expected temporal duration of its

366 sub-activities. $timelapse_{sub-activity}$ is also represented by a MOG of
367 $(\theta_{type}^{timelapse})$. The parameters of $timelapse_{sub-activity}$ are similar to pre-
368 vious sub-attribute $mixture_{sub-activity}$.

369 5.2.3 Recognition phase of the model

370 For a new unseen video dataset, we aim at recognising activities in an un-
371 supervised way. The task is achieved by measuring the similarity between
372 reference activity models that are learned for each type of discovered activity
373 using unlabelled training videos and a test activity model that is obtained
374 from the discovered activities of the new video.

375

376 First, a new sequence of Perceptual Feature Chunks are computed for the
377 new video. Second, using three levels of topology learned from training
378 videos, we create new *Primitive Events*. Thereby, $Transition_{PE}$ of new
379 *Primitive Events* are matched with the $Transition_{PE}$ of *Primitive Events*
380 used in training. Third, the activity discovery process is performed with
381 the new *Primitive Events* and a new sequence of discovered activities are
382 computed. Fourth, for each type of discovered activity of the new video, an
383 activity model is built as explained in Section 5.2.2. Finally, we compute a

384 score between the new model and learned models and classify the activity by
385 assigning the label of the best match.

386

387 To compute a similarity score between two activity models, we define a
388 metric in a recursive manner. At each level of the model, we calculate a
389 similarity score by computing the Euclidean distance between attributes and
390 sub-attributes of the nodes of two models at that level and append the simi-
391 larity score obtained from the finer level. Since the range of attributes vary,
392 we have normalised the distances. This recursive procedure give us the oppor-
393 tunity to have a similarity score at the root node that measure the similarity
394 of the models at all levels.

395 **6 Experimental results**

396 We have tested the proposed framework on three datasets. Each video in the
397 dataset contains one person and is recorded using a monocular video camera
398 with 640×480 pixels of resolution. The size of the person is about 50×150
399 pixels. The three datasets are as follows:

400

401 a) HOMECARE dataset: It consists of a set of 7 videos associated to seven
402 people performing everyday activities in an apartment (activities are listed
403 in Table 1-(a)). The apartment, which has a size of $42m^2$, is an experimen-
404 tal laboratory set up under the national project Gerhome. Each video is
405 of 4-hour length. An overview of the scene and a sample of activities are
406 presented in Figure 2-(a) and Figure 6, respectively.

407

408 b) HOSPITAL dataset: It includes a set of 4 videos associated to 4 pa-
409 tients and recorded in a hospital room, which has a size of $32m^2$, while the
410 patients are visiting their doctors. The patients perform some guided activi-
411 ties from a medical protocol. Figure 8-(e) shows the overview of the hospital
412 room and Figure 7 describes the set of activities that we aim to recognise.
413 Each video lasts 1 hour.

414

415 c) CHU dataset: It consists of a set of 30 videos associated to 30 patients
416 in the same room of HOSPITAL dataset. This dataset is more challenging
417 than HOSPITAL dataset, since the person performed a non-guided activities
418 of daily livings. The activities of interest are given in Figure 8-(a-d).

419

420 The classification results for HOMECARE and HOSPITAL datasets are
 421 based on leave-one-out cross validation. The evaluation is performed by
 422 learning the scene (Section 4.1.2) and activity (Section 5.2.2) models from the
 423 training videos and by recognising activities in a test video. In the HOME-
 424 CARE dataset, the scene and activity models are learned after processing
 425 6 videos. The remaining video from the HOMECARE dataset is used for
 426 recognition procedure. First, activities are discovered in the remaining video
 427 using the set of extracted *Primitive Events* associated to the person and
 428 the scene model learned from 6 videos. Then, for each discovered activity,
 429 an activity model is created and compared with the activity model learned
 430 from training videos (Section 5.2.3). Similarly, in the HOSPITAL dataset the
 431 scene and activity models are learned using 3 videos and one video is selected
 432 to recognise activities. For the CHU dataset, we have randomly selected 10
 433 videos for learning the scene and activity models. The remaining videos are
 434 used to recognise activities.

435 To evaluate the framework, we have used True Positive (TP), False Posi-
 436 tive (FP), False Negative (FN) and calculated *Sensitivity* and *Precision*
 437 as follows:

$$Sensitivity = \frac{TP}{TP + FN} \quad (11)$$

438

$$Precision = \frac{TP}{TP + FP} \quad (12)$$

439

440 An example of learned scene model for the HOMECARE dataset is repre-
 441 sented in Figure 2. The performance of our framework for HOMECARE,
 442 HOSPITAL and CHU datasets are displayed in Table 1-(a), Table 1-(b) and
 443 Table 1-(c), respectively. The recognition results of the proposed framework
 444 are obtained by comparing with manually annotated ground truths. It can
 445 be seen from Table 1 that the proposed method proved to be very reliable
 446 for activities between two areas (e.g. “armchair” to “table” in Table 1-(a),
 447 ”exercise 1” in Table 1-(b) and “office desk” to “drugs desk” in Table 1-(c)).
 448 The proposed method is also good at recognising activities occurring in one
 449 area (e.g. “reading in the armchair” in Table 1-(a), “preparing coffee” in
 450 Table 1-(b) and “preparing drugs” in Table 1-(c)). Thanks to the proposed
 451 hierarchical model of activities (section 5.2), we are able to recognise differ-
 452 ent activities performed within a particular area. For example, the Table
 453 1-(a) shows that the system has detected two different activities (standing
 454 and reading) when the person is in the armchair area (2^{nd} area for $k = 5$ in
 455 Figure 2-(b)). The discovery and distinction between two different activities

456 occurring in the same area are possible thanks to the use of the local dy-
457 namics (section 4.2.2). This can also be seen in Table 1-(b) where the two
458 different exercises (Up/down and Balance) occurring in the same area are
459 not confused.

460

461 The reason of failure in detecting an activity (i.e. False Negative) is the
462 failure in motion detection. The process of trajectory extraction described in
463 Section 4.1 sometimes fails to track people. Because of the inadequate tra-
464 jectory information, we have many FNs in CHU dataset. For HOMECARE
465 and HOSPITAL dataset, the false detection of an activity (i.e False Positive)
466 usually happens when the person stops an activity without changing his/her
467 place (e.g. the person stays still for a while at the end of eating activity).
468 Recognizing non-guided ADL is more challenging. In CHU dataset, we have
469 high FP rates because some of the learned zones are very close to each other.
470 For instance, for the actions of "preparing tea" and "talking on the phone",
471 we obtain a high rate of FP, because the zones where the actions occur in
472 are very close to each other. Therefore, these actions are misclassified.

473

474 Considering the results in Table 1, it can be seen that the framework achieves

475 a high rate of True Positive and a low rate of False Negative. In total, ma-
476 jority of the performed activities are recognised by the framework.

477

478 The concept of primitive events together with hierarchical activity models
479 also enables us to handle the problem of occlusion. In the case of occlusion,
480 as long as some motion is detected on the visible body parts we could be able
481 to create primitive events and, then, activity models. In severe cases, our
482 framework may miss some instances of primitive events. In fact, occlusion
483 is one of the reasons that causes FNs in Table 1. However, since we statis-
484 tically learn activity models, it is still possible to build the model from the
485 discovered activities (not occluded) and perform recognition.

486

487 We have also analysed the effect of the number of clusters in topology learn-
488 ing phase (k parameter in Section 4.1.2). We have tested the performance
489 of the proposed method by selecting different number of clusters. Table 2
490 shows the average sensitivity and precision values obtained by selecting the
491 number of clusters as 5,10,15; 7,10,15 and 7,11,16 in CHU dataset. It can be
492 seen that the number of clusters does not significantly affect the recognition
493 performance of the framework.

495 In Table 3, we have compared the proposed framework with our previous
496 work described in [28] and a rule-based method proposed in [35] where the
497 activities are manually modelled by setting rules and constraints. In [35],
498 they cannot differentiate finer activities inside an area (e.g, “sitting at the
499 table” and “eating“) and recognition performance for some activities are not
500 presented. Thus, for the method in [35], we have given only the results they
501 have presented and the accumulated recognition rate for merged activities.
502 The bold values in the table show the best result for each activity class. It
503 can be seen that for all activity classes the proposed method gives a better
504 rate of sensitivity and precision compared to the method in [35]. Unlike in
505 [35], it can be seen that the HAM is capable of differentiating finer activities.
506 Compared to the method in [28], the proposed HAM enables us to enhance
507 the recognition results. In two activities (“eating“ and ”preparing meal“) we
508 achieve better sensitivity and precision rates and in two activities (“inside
509 bathroom“ and ”from armchair to table“) we achieve better precision rates.

510 **7 Conclusion**

511 In this paper, we have proposed a complete unsupervised framework for dis-
512 covering, modelling and recognising activities of daily living using a fixed
513 camera in an unstructured scene. This framework includes all steps from
514 the low-level processing to the semantic interpretation of the motion in the
515 scene. Global and local human features are extracted from the video and
516 used to learn meaningful areas (topologies) of the scene in an unsupervised
517 way. Combining global and local features with topologies enables us to build
518 primitive events in the video at different levels of resolution. Following these
519 steps, we have proposed a new model for representing activities: Hierarchical
520 Activity Model which benefits from the multi-resolution structure in primi-
521 tive events.

522

523 The contributions of the framework are twofold: primitive events and hi-
524 erarchical activity models. To bridge the semantic gap we have proposed
525 an intermediate layer of primitive events which are used to link semantics
526 with perceptual information. Thanks to this intermediate layer, the proposed
527 method overcomes the problem of manually describing the target activities.
528 The hierarchical activity model give us the opportunity to categorize complex

529 activities using increasing granularity levels of the spatio-temporal structure
530 of basic activities.

531

532 This framework has been successfully tested for recognising ADL by exper-
533 imenting in an apartment and in a hospital room. Although there are some
534 missed activities because of failure in detecting finer motion, the experimental
535 results show that the framework is a successful system that can automati-
536 cally discover, learn and recognise ADL. In addition, it can be observed that
537 the framework can be used in medical applications in order to monitor older
538 persons suffering from Alzheimer or dementia. The statistical information in
539 HAM provides an important data to learn the normal behaviour models and
540 life pattern of people. Hence, the change in behaviour models can be easily
541 detected and used to evaluate the status of people. We believe that by using
542 motion descriptors such as HoG and HoF [21] we can capture finer motion
543 in the video and obtain better performance.

544

545 The framework can also be used in many other fields such as video surveil-
546 lance of metros and airports. Our future work is going to be the extension
547 of our framework to detect abnormal activities in such applications. In addi-

548 tion, we are going to test our framework in online-learning mode by updating
549 (or creating) the zones and activity models in time with new trajectory in-
550 formation.

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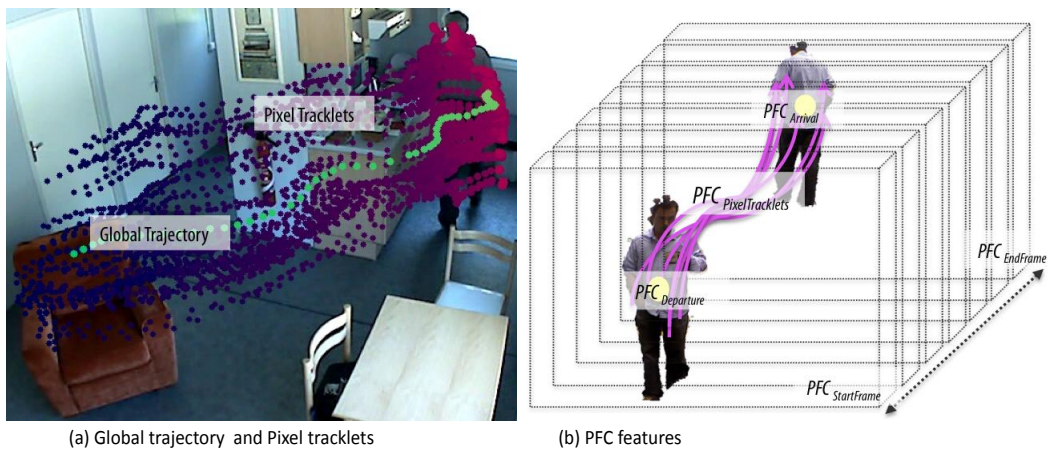
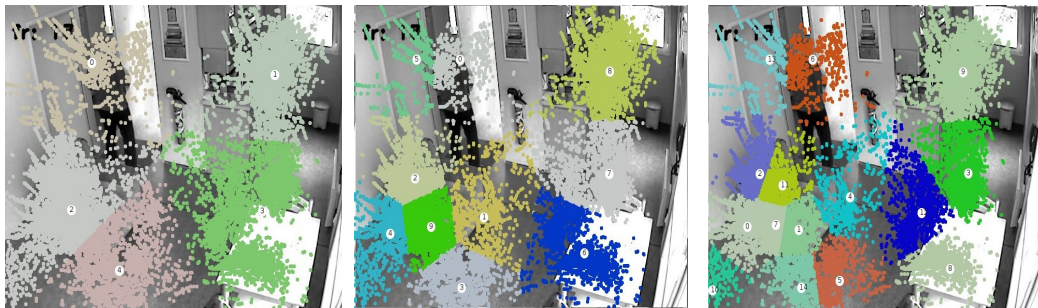


Figure 1: Global trajectories (green) and Pixel Tracklets (purple to pink) to construct Perceptual Feature Chunks.



(a) HOMECARE



5 clusters

10 clusters

15 clusters

(b)

Figure 2: (a) The empty scene for HOMECARE. (b) Example of the scene model with $l = 1, 2$ and 3 obtained by k-means clustering ($k = 5, 10$ and 15) for HOMECARE dataset described in section 6.

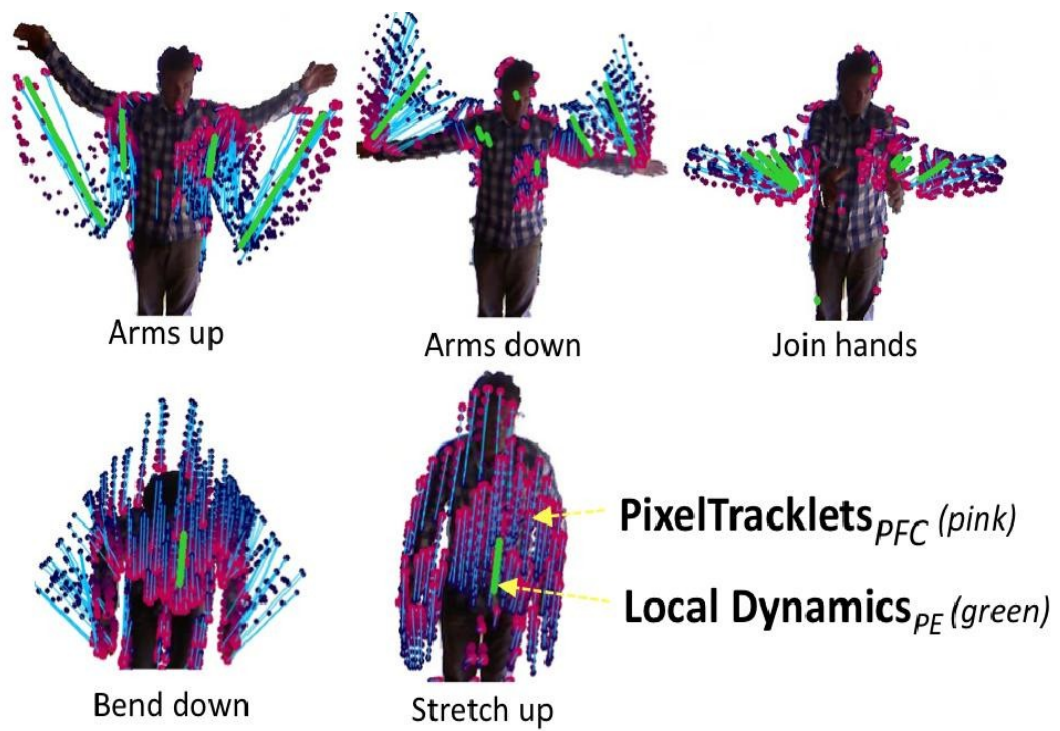


Figure 3: Example of the abstraction of $PixelTracklets_{PFC}$ (pink) into $LocalDynamics_{PE}$ (green). Each, $LocalDynamics_{PE}$ is displayed as a straight line corresponding to the start and end points of an abstracted tracklet (blue line).

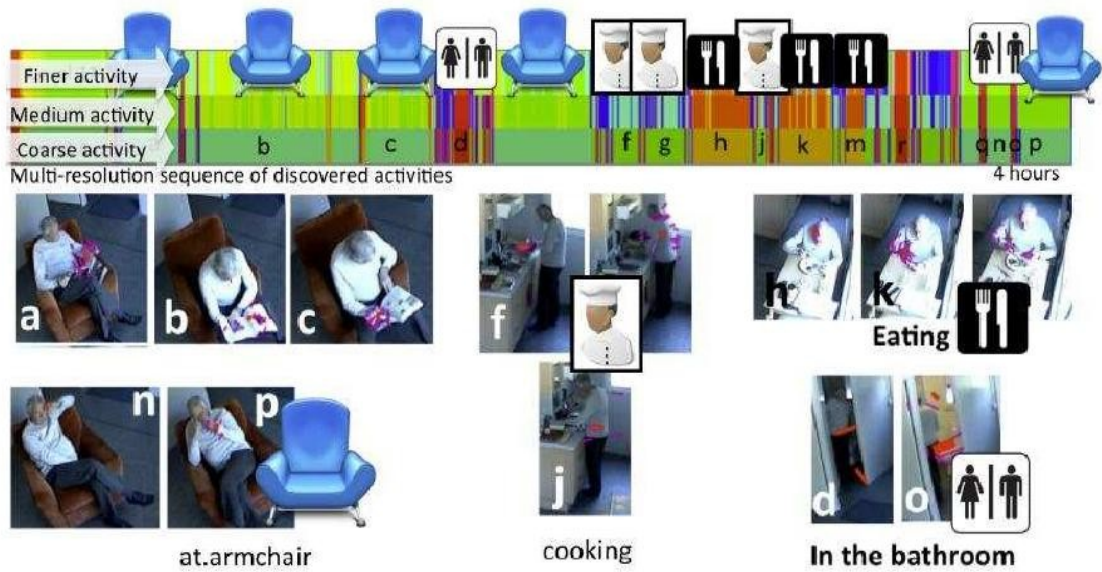
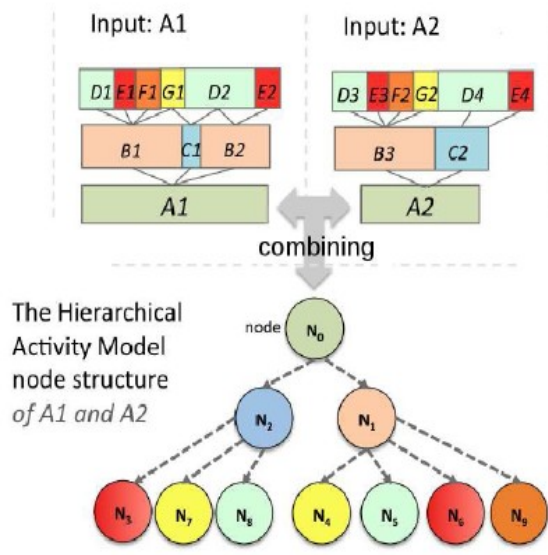
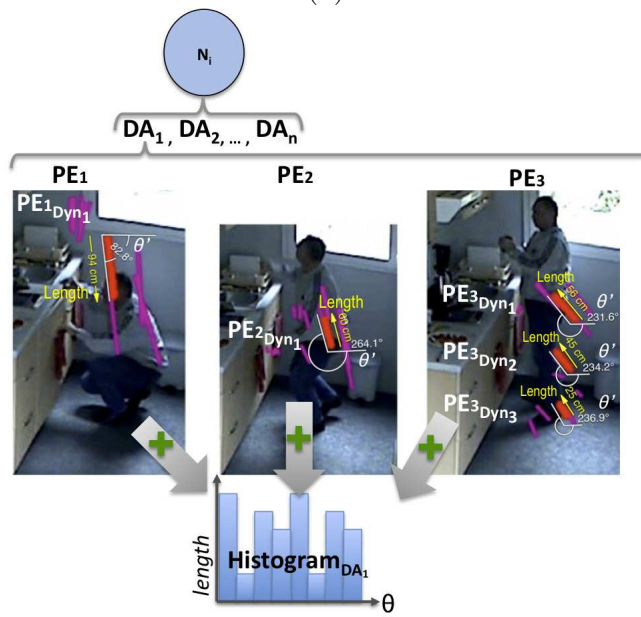


Figure 4: Example of discovered activities (coloured segments) for 4 hours video of one person performing everyday activities. 5 actions in the armchair (a, b, c, n and p), 3 cooking (f, g and j) and eating (h, k and m) actions and 2 actions in the bathroom (d and o) are discovered.



(a)



(b)

Figure 5: (a) Hierarchical Activity Model (HAM) constructed from all DA_s^l (i.e. $\{A_i\}_{1 \leq i \leq 2}$ for level 1, $\{B_i\}_{1 \leq i \leq 3}$ and $\{C_i\}_{1 \leq i \leq 2}$ for level 2 and $\{D_i\}_{1 \leq i \leq 4}$, $\{E_i\}_{1 \leq i \leq 4}$, $\{F_i\}_{1 \leq i \leq 2}$ and $\{G_i\}_{1 \leq i \leq 2}$ for level 3) (b) *Histogram of Local Dynamics* attribute computed from the set of discovered activities.

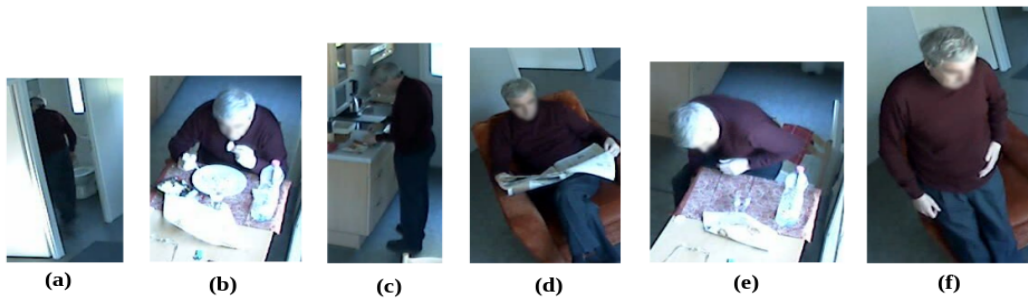


Figure 6: Everyday activities in HOMECARE dataset: (a) In the bathroom, (b) Eating, (c) Preparing meal, (d) Reading in the armchair, (e) Sitting at eating place, (f) Standing at armchair.

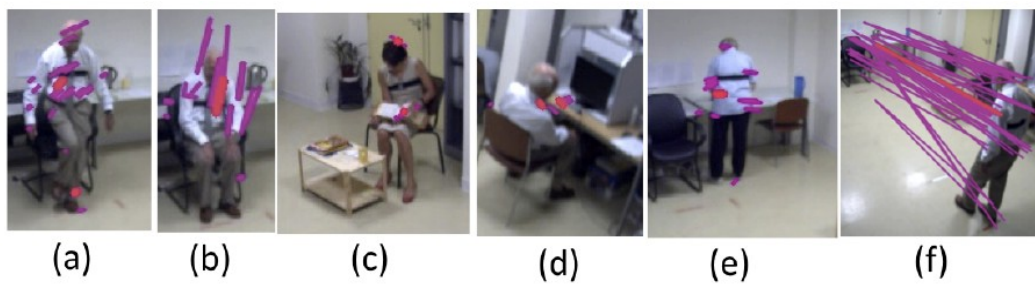


Figure 7: Guided activities in HOSPITAL dataset (a) Balance: Standing on one foot at at time, (b) Up/Down: Standing and sitting down in a continuous way, (c) Reading at the table, (d) At the computer, (e) Preparing coffee, (f) Exercise1/Exercise2: moving from the chair to a marked position and coming back.

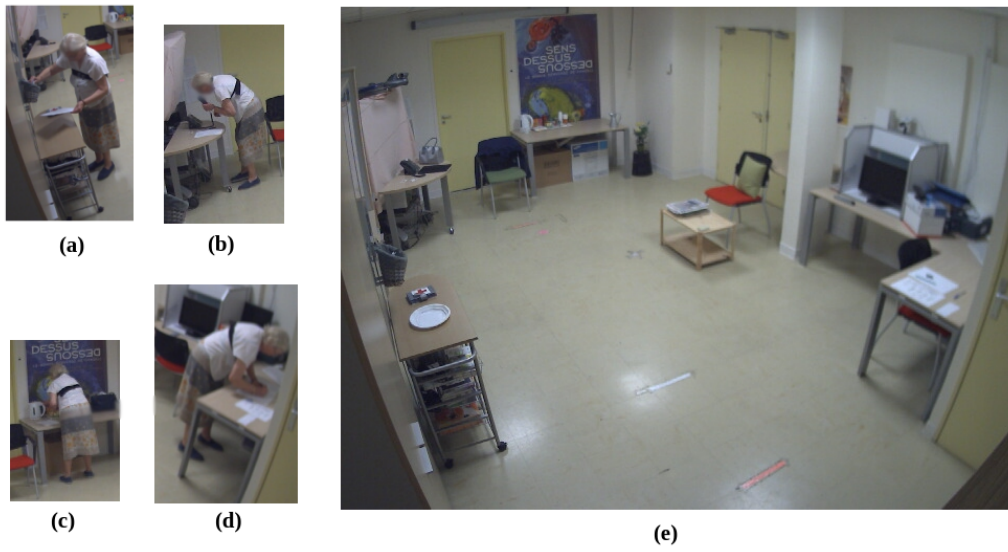


Figure 8: Non-guided activities in CHU dataset: (a) Preparing drugs, (b) Talking on the phone, (c) Preparing tea, (d) Paying bill. (e) Overview of the hospital room in HOSPITAL and CHU datasets.

Table 1: Recognition results for (a) HOMECARE, (b) HOSPITAL and (c) CHU datasets.

	TP	FP	FN	Sensitivity (%)	Precision (%)
Eating	31	1	0	100	96.87
Reading in the armchair	24	5	0	100	82.75
Preparing meal	54	2	1	98.18	96.42
Standing at armchair	11	2	0	100	84.61
Sitting at eating place	8	0	1	88.89	100
Inside the bathroom	14	2	0	100	87.5
From armchair to table	32	2	0	100	94.11
From armchair to kitchen	15	1	0	100	93.75

(a)

	TP	FP	FN	Sensitivity (%)	Precision (%)
Balance	3	0	0	100	100
Up/Down	3	0	0	100	100
Reading at the table	10	1	1	90.91	90.91
Preparing coffee	7	1	0	100	87.5
At the computer	6	1	0	100	85.71
Exercise 1	3	0	0	100	100
Exercise 2	3	0	0	100	100

(b)

	TP	FP	FN	Sensitivity (%)	Precision (%)
Preparing drugs	21	9	1	95.45	70
Talking on the phone	37	12	4	90.24	75.51
Preparing tea	53	11	10	84.12	82.81
Paying bill	40	8	9	81.63	83.33
From office desk to drugs desk	4	1	0	100	80
From drugs desk to tea desk	7	1	1	87.5	87.5

(c)

Table 2: Average sensitivity and average precision for three different level of clusters for CHU dataset.

Clusters	Average sensitivity (%)	Average precision (%)
5,10,15	87.74	77.56
7,10,15	84.06	75.99
7,11,16	80.43	78.37

Table 3: Comparison of recognition rates between the approach in [35], in [28] and the proposed method (specified as “HAM”) for HOMECARE dataset.

	[35]		[28]		HAM	
	Sensitivity (%)	Precision (%)	Sensitivity (%)	Precision (%)	Sensitivity (%)	Precision (%)
Eating	78.26	81.81	81	76	100	96
Sitting at eating place			88.88	100	88.88	100
Reading in armchair	85.96	80.32	100	85.71	100	82.75
Preparing meal	80	57.14	88	85	98.18	96.42
Standing at arm chair	-	-	100	84.61	100	84.61
Inside the bathroom	-	-	100	77.78	100	87.5
From armchair to table	-	-	100	88.89	100	94.11
From armchair to kitchen	-	-	100	93.75	100	93.75