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## Ecological Assessment of Autonomy in Instrumental Activities of Daily Living in Dementia Patients by the means of an Automatic Video Monitoring System

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1 ***i. Introduction***

2 One of the key features of Alzheimer’s disease (AD) is impairment in daily functioning as  
3 well as executive dysfunction due to global pathological changes in frontal and posterior areas  
4 (Marshall et al., 2006).

5 Recent studies show that in dementia patients, loss of functioning in Instrumental Activities of  
6 Daily Living (IADL) is strongly associated with faster cognitive decline (Arrighi et al., 2013)  
7 and in particular with poorer performances on executive function tasks (Katzmark et al.,  
8 2012; Razani et al., 2007) such as the Frontal Assessment Battery (FAB) (Dubois et al., 2000)  
9 or the Trail Making Test (version B) (Tombaugh, 2004). Hence, it represents an early  
10 predictor for cognitive deterioration and possibly even for conversion from Mild Cognitive  
11 Impairment (MCI) to AD (Reppermund et al., 2013).

12 The assessment of functioning in IADL attracts gradually more attention in clinical research  
13 and should be included not only as a part of diagnostic evaluation in dementia but it would  
14 also be essential to evaluate efficacy in rehabilitation settings (Clare et al., 2003; Cotelli et al.,  
15 2006).

16 Characterizing impairment in IADL is controversial because no standard exists so far as to the  
17 practical or theoretical definition (DeBettignies et al., 1990). Furthermore, until now, the  
18 assessment of IADL is mostly limited to questionnaires and rely often on informants reports,  
19 such as the Disability Assessment for Dementia scale (DAD), or the IADL scale of Lawton  
20 and Brody (Lawton et al., 1969) which suffer from biases and inaccuracies in informants’  
21 perceptions as well as the possibility that some older adults do not have an individual who can  
22 comment on their impact of cognitive impairment on routine activities. In general, existing  
23 functional assessments lack sufficient sensitivity to detect subtle functional changes or  
24 differences in behavior and therefore treatment effects (Gold, 2012). This leads to an urgent

25 need for better measures of functional changes in people with the earliest changes associated  
26 with AD in clinical trials (Snyder, 2014)

27 Besides, just a few of the named tools capture the earliest functional deficits seen in  
28 preclinical AD.

29

30 Growing recognition of the need for a more objective and direct measurement has led to  
31 some attempts to improve the assessments of IADL in clinical practice by developing new  
32 extensive informant-based computerized IADL questionnaire (Sikkes et al., 2012) or  
33 performance-based measures (Moore et al., 2007) which involve observing an individual  
34 enact an IADL, such as making a phone call or preparing his/her medications in either his  
35 natural or a clinical environment.

36 Farina et al. (2010) developed a new direct performance measure for patients with dementia,  
37 e.g. the functional living skills assessment (FLSA) (Farina et al., 2010). This tool was  
38 conceived to detect functional impairment targeting high-order social abilities in everyday-life  
39 and IADL by direct observation of the patient carrying out practical tasks or being verbally  
40 stimulated.

41 Nevertheless, those methods can be criticized as well first, for being still dependent on a  
42 human observer; secondly for removing the individual 's chosen routine and environmental  
43 cues that typically facilitate IADL. Finally, performance-based assessment can be often time-  
44 consuming (Sikkes et al., 2009) and represents a single evaluation data point compared with  
45 the multiple observations afforded by a questionnaire that comments on an individuals overall  
46 behavior through the last past weeks.

47 ICT and in particular automatic video analyses of patients carrying out various IADL  
48 could be an innovative assessment method (Robert et al., 2013) to help overcome those  
49 limitations in reducing the inter/intra-rater variability due to human interpretation and

50 increase ecological value by removing completely the human observer from the assessment  
51 site. Such techniques enable the patients' performances and actions in real time and real life  
52 situations to be captured and accurately evaluated and could provide the clinician with  
53 objective performance measures and a « second opinion » regarding the overall state of  
54 functionality of the observed subject.

55 In previous work, the use of such video sensor technology has been already  
56 demonstrated by König et al by showing significant correlations between manually as  
57 automatically extracted parameters and neuropsychological test scores as well as high  
58 accuracy rates for the detected activities (up to 89.47 %)(Konig, 2014). In a next step, we  
59 would like to investigate the use of video analyses for a completely automatized autonomy  
60 assessment based on the extracted video features.

61 In this line, the objective of this study is to investigate the use of ICT and in particular  
62 video analyses in clinical practice for the assessment of autonomy in IADL in healthy elderly  
63 MCI and AD patients by demonstrating an accurate automatized autonomy assessment based  
64 simply on automatically extracted video features from gait and IADL performances.

65

## 66 ***ii. Materials and Methods***

67 It is a non-randomized study involving 3 diagnosis groups of participants.

68 Several parameters will be obtained for each participant undergoing a so-called 'ecological  
69 assessment' consisting of the task to carry out physical tasks and a list of IADL. Those  
70 parameters reflect behavioral motion patterns during the assessment, such as trajectories and  
71 frequency of room zones that are possibly influenced by a patient's cognitive status.  
72 Furthermore, the amount of activities carried out completely and correctly, repetitions,  
73 omissions and execution time for certain complex activities such as managing medication will  
74 serve as an additional indicator for IADL functionality

75 *Study participants and clinical assessment*

76 Participants aged 65 or older were recruited within the Dem@care protocole at the Nice  
77 Memory Research Center located at the Geriatric department of the University Hospital.

78 The study was approved by the local Nice ethics committee and only participants with the  
79 capacity to consent to the study were included. Each participant gave informed consent before  
80 the first assessment.

81 The video data of 49 participants was exploitable from which 12 patients were diagnosed with  
82 AD, 23 patients diagnosed with MCI and 14 healthy controls (HC).

83 For the AD group, the diagnosis was determined using the NINCDS-ADRDA criteria  
84 (McKhann et al., 1984). For the MCI group, patients with a mini-mental state examination  
85 (MMSE) (Folstein, 1975) score higher than 24 were included using the Petersen clinical  
86 criteria (Petersen et al., 1999). Subjects were not included if they had a history of head trauma  
87 with loss of consciousness, psychotic or aberrant motor activity (tremor, rigidity,  
88 Parkinsonism) as defined by the Movement Disorder Society Unified Parkinson Disease  
89 Rating Scale (Fahn, 1987) in order to control for any possible motor disorders influencing the  
90 ability to carry out IADLs.

91

92 Each participant underwent a standardized neuropsychological assessment with a  
93 psychologist. In addition, clinical and demographical information were collected. In order to  
94 accurately stage the participants cognitive status, global cognitive functioning was assessed  
95 using the MMSE (Mini Mental State Examination) (Folstein, 1975). Other cognitive functions  
96 were assessed with the Frontal assessment battery (FAB) (Dubois, 2000) and the Free and  
97 Cued Selective Reminding Test (Buschke, 1984; Grober, 1987). Neuropsychiatric symptoms  
98 were assed using the Neuropsychiatric Inventory (Cummings, 1997) and functional abilities

99 were assessed using the IADL scale (IADL-E) (Lawton & Brody, 1969) during a clinical  
100 interview with the caregiver if there was one available.

101

### 102 *Clinical protocol*

103 One of the main goals of the Dem@care project is to develop a method to objectively assess  
104 decline in autonomy and in particular impairment of daily functioning in elderly people using  
105 Information and Communication Technologies (ICT) such as a video monitoring system and  
106 actigraphy. This could further lead to potential autonomy performance prediction.

107 The clinical protocol asked the participants to undertake first a set of physical tasks (Scenario  
108 1) and secondly a set of typical IADLs (Scenario 2) followed by a free discussion period  
109 while being recorded by a set of sensors. Scenario 1 consisted of a single walking task and a  
110 dual task. The dual task involves walking while counting backwards from ‘305’. These tasks  
111 intend to assess kinematic parameters of the participant via gait analysis (e.g., duration,  
112 number of steps, cadence, stride length). Scenario 2, also called the ‘ecological assessment of  
113 IADLs’, consisted of carrying out a set of daily living activities such as preparing a pillbox or  
114 writing a check within a timeframe of 15 minutes (see Table 1.) followed by a short  
115 discussion. The defined activities were based on commonly used IADL questionnaires and  
116 represent at once activities with high or low cognitive demand (in accordance with the Bayer  
117 Activities of Daily Living scale) (Erzigkeit et al., 2001; Hindmarch et al., 1998). The protocol  
118 was conducted in an observation room located in the Nice Research Memory Center, which  
119 was equipped with everyday objects for use in ADLs and IADLs, eg, an armchair, a table, a  
120 tea corner, a television, a personal computer, and a library. RGBD sensors (Kinect ®,  
121 Microsoft ©) were installed to capture the activity of the participants during the assessment.  
122 The aim of this protocol is an ecological assessment based on a ‘real time’ performance, that  
123 determines to which extent the participant could undertake independently a list of daily

124 activities within a timeframe of 15 minutes. All assessments were performed at the same time  
 125 of the day, between 2 pm and 3 pm.

126 A clinician verified the performance of each participant in terms of the amount of initiated  
 127 activities, correctly carried out activities as well as repetitions and omissions in order to  
 128 define the quality of each task execution. Accordingly to this performance verification and  
 129 based on previous work (Konig, 2014; Romdhane et al., 2012; Sacco et al., 2012) participants  
 130 were grouped (independently from their diagnosis group) into either ‘good’, ‘mediocre’ or  
 131 ‘poor’ performer.

132 All information were manually annotated and entered into the database via a tablet.

133 The rating of the videos was made by engineers specialized in video signal analysis working  
 134 at the Institut National de Recherche en Informatique et en Automatique (INRIA).

135

136 Table 1. Design of Ecological assessment

	<b>Part 1 Guided Activities (5 min)</b>	<b>Part 2 Semi Guided Activities (30 min)</b>	<b>Part 3 Discussion (5 min)</b>
<b>TASK TO PERFORM</b>	<u><b>Mono/Dual directed tasks</b></u> - Walking - Counting backwards - Both walking and counting backwards <u><b>Vocal directed tasks</b></u> - Sentence repeating task - Articulation control task	<u><b>List of ADLs/IADLs to organize and perform within 15mn</b></u> - Watering Plant - Preparing tea - Medication preparation - Managing finance (establishing account balance, writing a check) - Watching TV - Using Phone (answering, calling) - Reading Article and answering to questions	<u><b>Directed expression</b></u> Questions about tasks/progress of Scenario2 <u><b>Free expression and discussion</b></u> Verbal description of a picture Free discussion from the picture about the interest of the participant



- 
- Motor abilities: balance disorders
    - Cognitive abilities: flexibility, shared attention, psychomotricity coordination, answer time to a stimulus, working memory
  - Cognitive abilities: flexibility, planification, shared attention, psychomotricity coordination, work memory, time estimation, answer time to a stimulus
    - ADL/IADL performance
  - Cognitive abilities: working memory, short term memory, denomination ability (language), verbal fluency
    - Mood disorders (lack of motivation)
- 

137

138 *Data collection & Processing*

139 Participants had their activity recorded using a RGBD sensor, placed closest to the ceiling of  
 140 the ecological room to maximize scene coverage. Sensor data was posteriorly analyzed to  
 141 automatically extract gait data (e.g., stride length, number of steps, distance travelled) and  
 142 derive information from the automatically recognized instrumental activities of daily living  
 143 (IADL, duration and frequency, missed activities). The extracted data were then used as  
 144 input-features for Naïve Bayes classifiers trained for the classification of patient into  
 145 autonomy and dementia classes, separately.

146

147 An Event Monitoring System (see Figure 1.) using a RGBD sensor as input takes and  
 148 processes patient recordings and outputs gait parameters and the instrumental activities of  
 149 daily living (IADL) performed by the protocol participant.

150

151 *Figure 1. System Architecture*

152

153 *Event Monitoring System*

154 The event monitoring system is composed of four main modules: people detection, people  
 155 tracking, gait analysis and event modeling. People detection step is performed by the  
 156 background-subtraction algorithm proposed by Nghiem and Bremond (Nghiem, 2014). The

157 set of people detected by this module is then tracked over the scene by the algorithm of Chau  
158 et al. (Chau, 2011). The output of these two modules is then used as input for gait analysis  
159 and event recognition. The latter module is based on the work of Crispim-Junior et al.  
160 (Crispim-Junior, 2013), where an constraint-based ontology language is employed to model  
161 daily living activities in terms of posture, motion and location of the participant in the scene.  
162 Figure 1 presents an example of event model for the recognition of Preparing Drink event.  
163 Briefly, an IADL event model is conditioned on the recognition of a set of event models that  
164 model one activity-related aspect each. For instance, the event model for “Prepare Drink”  
165 activity is based on the recognition of two sub-events (components): the person is where  
166 drinking objects are placed (named Person\_in\_zone\_Drink) and the person exhibiting the  
167 posture “bending” (named Person\_bending). Both components intervals also need to be  
168 recognized (happen) at the same time (c1->Interval AND c2->Interval). For more details on  
169 IADL event modeling, please refer to Crispim-Junior et al (Crispim-Junior, 2013). Figure 2  
170 presents the definition of the explained event model following the ontology language.

171 Based on the data of previously described modules the gait analysis algorithm extracts fine-  
172 grained features (like stride length, distance travelled, and cadence) about gait patterns during  
173 specific events (*e.g.*, Mono and Dual tasks). The gait analysis data is then combined with  
174 information derived from the set of IADLs recognized by the Event Monitoring System  
175 (EMS) (*e.g.*, frequency and duration of performed activity, missed activities). The ensemble  
176 of data automatically extracted and derived by the system from the participant activities  
177 composed the behavioral data about the participant performance.

178

179 Figure 2. Event model for Preparing Drink Activity

180

181

182 Figure 3. Event recognition based on Activity zones. The left image presents the contextual  
183 zones used to describe the scene semantics. The right image presents an example of output of  
184 the EMS system.

185

186

187

### 188 *Autonomy Assessment and Dementia Diagnosis Classification*

189

190 Using the behavioral data extracted by the EMS we trained two Naïve Bayes models to  
191 classify participant performance in the clinical protocol according to a Dementia and an  
192 Autonomy class. To learn and validate the classification Models we employed a 20-fold  
193 cross-validation scheme, where we partitioned the data set into k equal parts and then iterate  
194 20 times where at each iteration one of the k folds were kept for parameter validation and the  
195 remaining k-1 were used for model learning. Model performance results correspond to the  
196 average of performance of the k validation folds. All classification experiments were  
197 performed using WEKA platform (Hall, 2009). The Naïve Bayes implementation used in  
198 WEKA is described in John and Langley (John, 1995). Although Naïve Bayes classifier  
199 assumes conditionally independence among input-parameters, an assumption that prove to be  
200 unrealistic most of the times in practical application, this classifiers tend to perform  
201 reasonably well compared to more sophisticate methods (e.g., support vector machines)  
202 (Huang, 2003; John, 1995) but it with a much smaller running time (Matwin, 2012).

203 A wrapper feature selection scheme was carried out a priori for feature subset selection based  
204 on best first search and Naïve Bayes classifier, which aimed at finding the optimal feature set  
205 for each classification task (Hall, 2003; Kohavi, 1997). The feature set with highest  
206 performance in this step was selected to compose the participant behavioral profile. Although  
207 these classifiers have been learned selecting the most relevant features from a common pool  
208 of features obtained using the AVMS, they were learned and operated independently.

209 *Autonomy and Diagnosis Classes*

210 The recorded data set was explored to evaluate the system performance on event monitoring  
211 and to classify the patients according to their Autonomy performance on the IADL scenario  
212 (Good, Mediocre and Poor) and their Diagnosis (Healthy, MCI and Alzheimer). Physical  
213 tasks and IADL monitoring: 49 participants of 65 years and over were recruited by the  
214 Memory Centre (MC) of a CHUN. The clinical protocol asks the participants to undertake a  
215 set of physical tasks and Instrumental Activities of Daily Living in a Hospital observation  
216 room furnished with home appliances Experimental recordings used a RGBD camera (Kinect  
217 ®, Microsoft ©). Autonomy classes are: Good, Mediocre or Bad; and Dementia classes are  
218 Healthy, MCI or Alzheimer.

219

220 *Statistical analyses*

221 Comparison between the two groups (e.g. HC subjects, MCI patients and AD group good  
222 performer, mediocre and poor performer) was performed with Mann-Whitney tests for each  
223 outcome variable of the automatic video analyses. Differences were reported as significant if  
224  $p < 0.05$ . Spearman's correlations were further performed to determine the association  
225 between the extracted video parameters and established assessment tools in particular for  
226 executive functioning, e.g. the FAB.

227

228 **iii. Results**

229 *Population*

230 14 HC subjects (age =  $74.1 \pm 6.62$ ), 23 MCI (age =  $77.6 \pm 6.17$ ) and 12 AD subjects (age =  
231  $82. \pm 8$ ) were included. Table 2 shows the clinical and demographic data of the participants.  
232 Significant intergroup differences in demographic factors were found for age between MCI  
233 and AD subjects as well as between HC and AD subjects ( $p < .05$ ). Further, significant

234 differences were found between all groups for the MMSE score, with a mean of 28.4 ( $\pm$  1.1)  
 235 for the HC group, 25.5 ( $\pm$  2.1) for the MCI group and 22.67  $\pm$  3.6 for the AD group ( $p < .05$ ).  
 236 Significant differences were found for FAB results between HC subjects with 16.3 ( $\pm$  1.1) and  
 237 MCI subjects with 14 ( $\pm$  2.4), as well as between HC subjects and AD subjects with 12.33 ( $\pm$   
 238 3.1) ( $p < .05$ ). The mean IADL scores did not differ between groups, with a mean IADL  
 239 score of 7 ( $\pm$  1.2) for the HC group, 6.33 ( $\pm$  1.7) for the MCI group and (6  $\pm$  1.8) for the AD  
 240 group.

241

242 Table 2. Characteristics and group comparisons for HC, MCI and AD subjects. Group  
 243 comparisons were made using Mann-Whitney U test ( $p < 0.05$ )  
 244

Characteristics	All subject N = 49	Healthy Control group N= 14	MCI group N= 23	AD group N= 12
Female, n (%)	26 (53.1%)	9 (64.3%)	10 (43.5%)	7 (58.33%)
Age, years mean $\pm$ ST	77.7 $\pm$ 7.3 <sup>†‡</sup>	74.1 $\pm$ 6.6	77.6 $\pm$ 6.2	82. $\pm$ 8
<b>Level of Education, n (%)</b>				
Unknown	0 (0%)	0 (0%)	0 (0%)	0 (0%)
No formal education	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Elementary school	16 (32.6%)	2 (14.3%)	5 (21.7%)	9 (75%)
Middle school	9 (18.4%)	2 (14.3%)	6 (26.1%)	1 (8.3%)
High school	8 (16.3%)	4 (28.6%)	4 (17.4%)	0 (0%)
Post-secondary education	16 (32.6%)	6 (42.9%)	8 (34.8%)	2 (16.7%)
MMSE, mean $\pm$ SD	25.6 $\pm$ 3.1 <sup>*†‡</sup>	28.4 $\pm$ 1.1	25.5 $\pm$ 2.1	22.67 $\pm$ 3.6
FAB, mean $\pm$ SD	14.25 $\pm$ 2.7 <sup>*‡</sup>	16.3 $\pm$ 1.1	14 $\pm$ 2.4	12.33 $\pm$ 3.1
FCSR Test	39.2 $\pm$ 9.9 <sup>*‡</sup>	46.27 $\pm$ 1.9	38.19 $\pm$ 7.2	29.50 $\pm$ 16.7
IADL-E, mean $\pm$ SD	6.4 $\pm$ 1.3	7 $\pm$ 1.2	6.33 $\pm$ 1.7	6 $\pm$ 1.8
NPI total, mean $\pm$ SD	6.89 $\pm$ 8.1 <sup>†‡</sup>	3.54 $\pm$ 2.8	5.77 $\pm$ 7.1	12.6 $\pm$ 11

245

246

#### 247 *Ecological assessment results*

248 The participants performed differently on the IADL scenario in terms of initiated and  
 249 successfully completed activities in accordance with their cognitive status.

250 The parameter ‘activities initiated’ correlated significantly with neuropsychological test results  
 251 namely the MMSE ( $p < 0.01$ ), FAB score ( $p < 0.01$ ), FCSR ( $p < 0.05$ ) and the IADL-E score  
 252 ( $p < 0.05$ ). In the same line, the parameter ‘activity completed’ correlated significantly with  
 253 the test results, MMSE ( $p < 0.01$ ), FAB score ( $p < 0.01$ ), FCSR ( $p < 0.05$ ) and the IADL-E  
 254 score ( $p < 0.05$ ). The obtained correlation analyses results are presented in Table 3. None of  
 255 the extracted parameters correlated with the NPI total scores.

256  
 257

258 Table 3. Correlation between IADL scenario performance and conventional cognitive  
 259 assessments (Spearman’s correlation coefficient)

260

<b>leo analyses data</b>	<b>MMSE</b>	<b>FAB</b>	<b>FCSR</b>	<b>NPI</b>	<b>IADL-E</b>
Spearman correlation coefficient (r) / p-values					
activities initiated	0.650** p=0.000	0.519** p=0.000	0.380* p=0.019	-0.177 p=0.234	0.324* p=0.030
activities completed	0.685** p=0.000	0.620** p=0.000	0.356* p=0.028	-0.266 p=0.071	0.334* p=0.025

261

262 After the performance analyses, the participants were classified based on their IADL  
 263 performance. The cut-off scores between the classes have been based on the observation of  
 264 the analyses of the participant’s performances in terms of completely carried out activities,  
 265 and on the cumulative frequencies of the completely carried out activities. These were  
 266 divided in equal parts, as homogeneously as possible in terms of data coverage following the  
 267 frequency curve as presented in Figure 2.

268

269 Figure 4. Cumulative frequency curve of completed carried out activities

270

271

272 This division into three equal classes resulted in the following cut-off scores:  
 273 From 13 to 8 completed activities was a good performance, meaning highly independent;  
 274 from 7 to 4 completed activities was a mediocre performance; and below 4 completed  
 275 activities was a poor performance, representing highly dependent in daily living activities.  
 276 The grouping of the participants was done blinded from their diagnosis group in order to  
 277 avoid classification biases, i.e. more likely to classify a HC as a 'good' performer. A HC  
 278 subject could sometimes show a mediocre IADL performance on the assessment and in turn a  
 279 MCI subject could show a good IADL performance. Taking into consideration that the  
 280 objective of the assessment was to stage autonomy levels and not necessarily disease  
 281 progression, even though they are associated, it was important to make that differentiation.  
 282 Table 4 shows the classification results based on the participants IADL scenario performances  
 283 with their diagnosis group, as well as their average amount of completely carried out  
 284 activities. Twenty-two participants from which 13 HC and 9 MCI subjects with an average of  
 285 10.04 correctly carried out activities were classified as good performer, 16 participants from  
 286 which 1 HC, 10 MCI and 5 AD subjects with an average of 5.5 correctly carried out activities  
 287 were classified as mediocre performer and 11 participants from which 4 MCI and 7 AD  
 288 patients with an average of 1.5 correctly carried out activities were classified as poor  
 289 performer.

290

291 Table 4. Ecological Assessment results

	<b>N</b>	<b>HC</b>	<b>MCI</b>	<b>AD</b>	<b>Activites completed (in mean <math>\pm</math>SD)</b>
<b>Good performance</b>	22	13	9	-	10.04 $\pm$ 1.4
<b>Mediocre performance</b>	16	1	10	5	5.5 $\pm$ 1.2
<b>Poor performance</b>	11	-	4	7	1.54 $\pm$ 1.4

292

293

294 *Automatic video monitoring results*

295 Table 5 presents the results of the evaluation of the Automatic Video Monitoring System  
296 (AVMS) with respect to its precision at detecting correctly the events of the clinical protocol  
297 (scenario 1: Single and Dual task and scenario 2: the number of activities of daily living)  
298 annotated by domain experts while watching the experiment video.

299

300

301

Table 5. Activity/Event Detection Performance

<b>Events</b>	<b>Recall</b>	<b>Precision</b>
<i>Scenario 01</i>		
<b>Mono Task</b>	1	0.88
<b>Dual Task</b>	1	0.98
<i>Scenario 02</i>		
<b>Searching Bus line</b>	0.58	0.625
<b>Medication preparation</b>	0.87	0.93
<b>Watering Plant</b>	0.8	0.63
<b>Reading Article</b>	0.6	0.88
<b>Preparing Drink</b>	0.90	0.68
<b>Talk on Phone</b>	0.89	0.89

302

303 Scenario 1, the single and dual task obtained the precision rates of 88% and 98%.

304 From all proposed activities, ‘Medication preparation’ was detected with the highest precision  
305 of 93 % followed by ‘Using the phone’ with 89% and ‘Reading an article with 88%.

306

307

308 *Automatized classification of participant cognitive status*

309 We compared the results for the percentage of patients correctly classified. For the three  
310 classifiers the data set is the same and contains 49 patients in total. The overall activities were  
311 correctly automatically detected with high sensitivity and precision results as previously  
312 described. Based on the automatically extracted behavioral data (see the list below), two



313 different classifiers were learned: one for dementia diagnosis and the other for autonomy  
314 assessment (see Table 6).

315 The classification procedure was intrinsically based on the features automatically extracted  
316 from the physical tasks and IADLs performed by the participant during the clinical protocol.  
317 For comparison purposes we have also learned the same classifier but only with behavioral  
318 data from the physical task and only with IADL derived data. We hypothesized that  
319 combining the two scenarios of the protocol could increase the accuracy of the classification  
320 since they would provide complementary information about a participant performance at daily  
321 living activities, e.g., motor and cognitive performances.

322 In the Autonomy classification task the following features were employed:

- 323 • *\_ Single Task Total Duration,*
- 324 • *\_ Single Task Gap Duration,*
- 325 • *\_ Single Task Standard Deviation Steps,*
- 326 • *\_ Dual Task Gap Duration.*
- 327 • *\_ Dual Task Max Steps,*
- 328 • *\_ Person using PharmacyBasket Frequency of Event (frequency),*
- 329 • *\_ Person using PharmacyBasket Duration of Event (seconds).*

330

331 For the Diagnosis classification, a different set of features has been identified:

- 332 • *\_ Age,*
- 333 • *\_ Single Task Average Steps,*
- 334 • *\_ Single Task Speed Average from Centroid Information,*
- 335 • *\_ Dual Task Max Steps,*
- 336 • *\_ Dual Task Min Steps,*
- 337 • *\_ Person reading inChairReadingTable Duration of Event (Frames),*

338

339 The classifier for Dementia Diagnosis task obtained an accuracy of 61.22% when using only  
340 features based on IADL (Scenario 2), and of 75.51% when just extracting features from  
341 Scenario 1, the physical tasks. The accuracy rate increased up to 73.46% when combining  
342 features from both scenarios. However, the higher recognition rates were found for the  
343 Classifier learned from the group of patients sorted by autonomy class; based on simply the

344 automatically extracted video features from scenario 2, 77.55% accuracy was obtained and  
 345 75% accuracy for scenario 1. The highest accuracy rate of 83.67% was obtained when  
 346 combining directed tasks and IADLs.

347

348 Table 6. Classification results

<i>Autonomy assessment</i>	<b>Input Data</b>		
<i>Performance</i>	<b>Scenario 01</b>	<b>Scenario 02</b>	<b>Both Scenarios</b>
Correctly Classified Instances	37 (75.5102 %)	38 (77.551%)	41 (83.6735%)
Incorrectly Classified Instances	12 ( 24.4898 %)	11 (22.449%)	8 (16.3265%)

349

<i>Diagnosis assessment</i>	<b>Input Data</b>		
<i>Performance</i>	<b>Scenario 01</b>	<b>Scenario 02</b>	<b>Both Scenarios</b>
Correctly Classified Instances	36 (73.4694%)	30 (61.2245%)	36 (73.4694%)
Incorrectly Classified Instances	13 (26.5306%)	19 (38.7755%)	13 (26.5306%)

350

351

352

353 ***iv. Discussion***

354 The present study suggests that it is possible to assess autonomy in IADL functioning with the  
 355 help of an automatic video monitoring system and that simply based on the extracted video  
 356 features different autonomy levels can be classified highly accurately. The results obtained  
 357 are significantly high for a correct assessment of autonomy but also cognitive status in terms  
 358 of diagnosis. This means, that 'the proposed system' may become a very useful tool providing  
 359 clinicians with diagnostic relevant information and improve autonomy assessment in AD or  
 360 MCI patients in real time decreasing observer biases.

361

362 The results demonstrate that all extracted elements of the clinical protocol, the kinetic  
 363 parameters from the single and dual task, as well as the selected features from the IADL task,  
 364 are important to take into consideration in the automatized analyses in order to assess and  
 365 further predict accurately autonomy performance of patients. In fact, adding features from the  
 366 very standardized directed tasks to the classification analyses even increased the accuracy

367 rates for diagnosis but even more for the autonomy groups. This means that in extractable gait  
368 features such as ‘Single Task Standard Deviation Steps’ and ‘Dual Task Gap Duration’ lies  
369 relevant information about a patient’s capacity to perform IADLs and therefore his or her  
370 autonomy level. These features added up to the automatically detected lengths and  
371 frequencies of the to carry out activities result in a highly accurate autonomy classification  
372 rate of almost 84%, allowing soon an almost fully automatized functional assessment in  
373 clinical practice. The work of Gillain et al. illustrates in the same manner that it may be  
374 possible to determine different cognitive profiles, and hence autonomy levels, by the  
375 measurement of gait parameters (Gillain, 2009). This confirms previous research findings that  
376 gait ability and cognitive functions are interrelated, and in particular executive functions and  
377 gait speed (Beauchet et al., 2013; Doi et al., 2013; Doi et al., 2014; Montero-Odasso et al.,  
378 2009). Gait impairment is already known to be a common characteristic of patients with MCI  
379 (Allan et al., 2005) and represents a risk factor for conversion to AD (Buracchio et al., 2010;  
380 Verghese et al., 2007). Therefore, changes in these motor function may be useful in the early  
381 detection of dementia during preclinical stages and easily measurable by sensor technologies.

382         Furthermore, significant correlations were found between the parameters of initiated  
383 and completed activities and most neuropsychological test results, particularly with MMSE  
384 and FAB scores showing that group differences even with just a small sample size could be  
385 detected when using such techniques, and this when regular assessment tools such as the  
386 IADL-E questionnaire lacked sensitivity to detect these group differences.

387 Finally, high activity detection rates, up to 93% for the ‘Medication preparation’ activity,  
388 could be achieved validating further the use of AVMS for evaluation and monitoring  
389 purposes.

390 The study’s results were consistent with previous work where with a sensitivity of 85.31 %  
391 and a precision of 75.90% the overall activities were correctly automatically detected (Konig

392 et al., 2015) although the present study was with a larger cohort and included as well AD  
393 patients.

394 Similar work, hence quantitative assessments of IADL performance, has been done using a  
395 different technique by Wadley et al. with the results that across timed IADL domains, MCI  
396 participants demonstrated accuracy comparable with cognitively normal participants but took  
397 significantly longer to complete the functional activities (Wadley et al., 2008).

398 This suggests that slower speed of task execution could be an explanation for the differences  
399 found in the extracted features and thus, represent an important component and early marker  
400 of functional change already in MCI patient. A component that would not be detected by  
401 using traditional measurements of daily function but easily by the AVMS.

402 Likewise, Stucki et al. proved feasibility and reliability of a non-intrusive web-based sensor  
403 system for the recognition of Activities of Daily Living (ADL) and the estimation of a  
404 patient's self-dependency with high classification precision rates (up to 90%) (Stucki et al.,  
405 2014). Bang et al. used multiple sensor fusion (pressure sensors, passive infrared sensors and  
406 worn accelerometers) for automatized ADL detection with achieved accuracy rates of up to  
407 90% (Bang et al., 2008). Nevertheless, these studies were carried out with a very small group  
408 sample of healthy and in average younger participants.

409

410       Until now, the clinical assessment of functional changes in AD and MCI patients has  
411 traditionally relied on scales and questionnaires that are not always sensitive to the earliest  
412 functional changes. This leads to an important need to develop improved methods/techniques  
413 to measure these changes, ideally at the earliest stages. Therefore, recently research efforts  
414 have been placed on studies finding new innovative and more objective ways to measure  
415 functional and cognitive changes associated with AD (Goldberg et al., 2010; López-de-Ipiña,

416 2012; Vestal et al., 2006; Yakhia et al., 2014; Zola et al., 2013).

417

418         The main interest of the present study was to demonstrate the practical application of  
419 the use of such a video monitoring system in clinical practice. Now, once the system's use  
420 has been validated by significant correlation with neuropsychological test scores, particularly  
421 for executive functioning, and highly accurate detection rates, it can be employed as a  
422 supportive assessment tool within clinical routine check-ups and even move on to more  
423 naturalistic environments such as nursing homes.

424         The systems' extracted information can provide the clinician with direct measurements  
425 (see the list of features) indicating, once interpreted, a certain level of autonomy performance,  
426 as well as with information about possible underlying mechanisms caused by decline in  
427 certain cognitive functioning, namely executive functions which are highly  
428 associated (Marshall et al., 2011). This technique has the advantage of leaving out the  
429 clinician, who represents often in assessments a potential stress factor, completely from the  
430 evaluation site, and thus increasing ecological validity by leaving the patient alone in a more  
431 naturalistic 'living-room alike' setting. The use of sensors for the measurement of behavioral  
432 patterns reduces important assessment biases often present in clinical practice and adds  
433 objective value to the assessment procedure.

434         The objective on a long term is to provide a stable system that allows to monitor  
435 patients and their autonomy at home over a longer period. The within this study validated  
436 parameters can serve as indicators for illness progression, decline in IADL performance and  
437 hence, executive functions detectable with the help of new technologies much earlier, before  
438 somebody in the family would notice and send the patient to a specialist.

439         The limitation of this study resides firstly in the recruitment process; the AD population  
440 was older than the other groups, because in our clinical practice it was quite difficult to recruit  
441 young AD patients but the age difference might have had an impact on their motor behavior.

442 Therefore, in future studies it would be important to also focus on recruiting younger AD  
443 patients in order to control for this variability. Secondly, the HC subjects were recruited  
444 through the Memory Center which means that most of the HC participants came to the centre  
445 with a memory complaint even though in their neuropsychological tests they performed  
446 within normal ranges. It has to be taken into consideration that those participants may not be  
447 completely healthy and suffer from a higher risk to convert to MCI than people that do not  
448 consult the center for a memory complaint (Jacinto et al., 2014).

449         It has to be further underlined that even if participants were alone during the IADL  
450 assessment, the simple fact of knowing that they were recorded could have had an impact on  
451 their stresslevel and thus, their performance.

452

453 To conclude, according to the recently published review of Snyder et al, research efforts have  
454 launched large prevention trials in AD and these efforts have further clearly demonstrated a  
455 need for better and more accurate measures of cognitive and functional changes in people  
456 already in the earliest stages of AD (Snyder et al., 2014). In the same line, the US Food and  
457 Drug Administration elevated the importance of cognitive and functional assessments in early  
458 stage clinical trials by proposing that even in the pre-symptomatic stages of the disease,  
459 approval will be contingent on demonstrating clinical meaningfulness.

460         Similiarly, Laske et al. argued that there is an increasing need for additional  
461 noninvasive and/or cost-effective tools, allowing identification of subjects in the preclinical or  
462 early clinical stages of AD who could be suitable for further cognitive evaluation and  
463 dementia diagnostics (Laske et al., 2014). Once examined in ongoing large trials, the  
464 implementation of such tools may facilitate early and potentially more effective therapeutic  
465 and preventative strategies for AD.

466 All this points out, the need for improved cognitive and functional outcome measures for

467 clinical of participants with preclinical AD and those diagnosed with MCI due to AD. With  
468 our study, we propose a new method of measuring objectively and accurately functional  
469 decline in patients from the earliest stages on with the support of the vision sensor  
470 technologies; a reliable method that could potentially, once validated through larger scale  
471 cohort studies, serve within clinical trial of new drug interventions as an endpoint measure to  
472 prove their effects on ADL function. Finally, the use of such systems could facilitate and  
473 support aging-in-place and improve medical care in general for these patients.

474

475

#### 476 **Conflict of Interest Statement**

477 Authors declare that the research was conducted in the absence of any commercial or  
478 financial relationships that could be constructed as a potential conflict of interest.

479

480

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Figure 1.JPEG

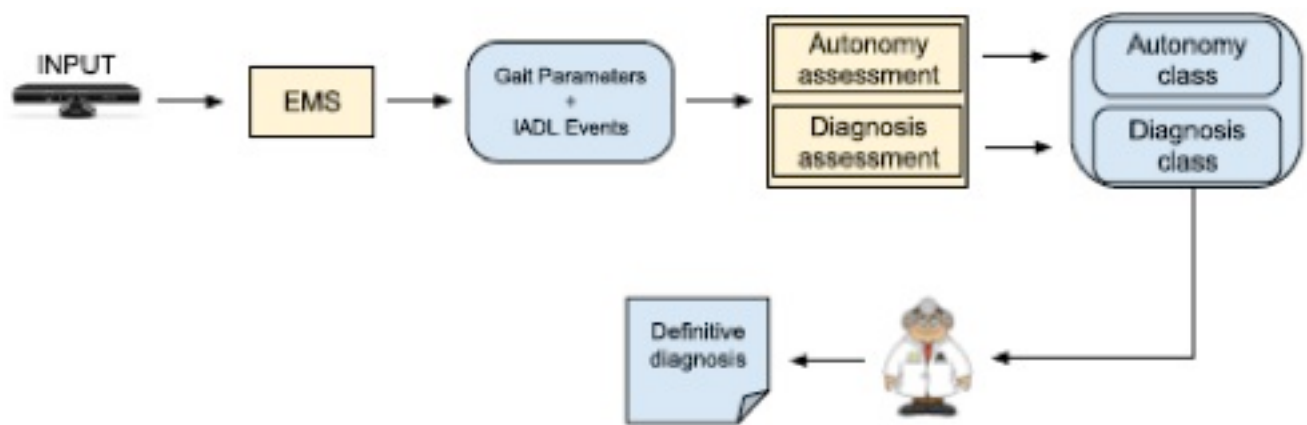


Figure 2.JPEG

Composite Event (Prepare Drink),

Physical Objects (Person: p1) (Zone: zDrink )

Components (

(c1 : PrimitiveState Person\_in\_zone\_Drink(p1,zDrink)

(c2 : PrimitiveState Person\_bending (p1) )

)

Constraints( (c1->Interval AND c2->Interval

(duration (c1) > 5 )

Alarm (URGENT )

Figure 3.JPEG

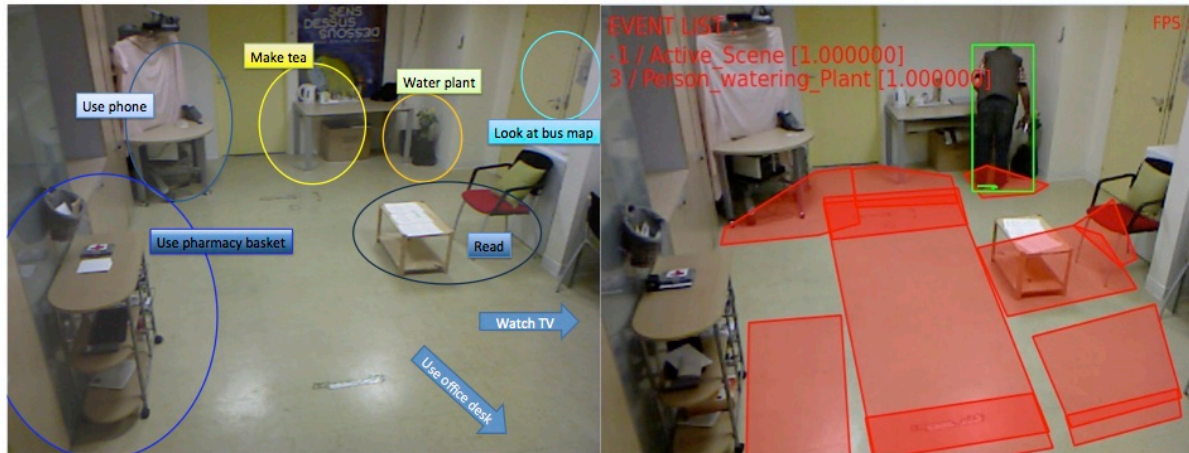


Figure 3. Event recognition based on Activity zones. The left image presents the contextual zones used to describe the scene semantics. The right image presents an example of output of the EMS system.

Figure 4.JPEG

