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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

	Part 1 Guided Activities (5 min)	Part 2 Semi Guided Activities (30 min)	Part 3 Discussion (5 min)
TASK TO PERFORM	<u>Mono/Dual directed tasks</u> - Walking - Counting backwards - Both walking and counting backwards <u>Vocal directed tasks</u> - Sentence repeating task - Articulation control task	<u>List of ADLs/IADLs to organize and perform within 15mn</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>Directed expression</u> Questions about tasks/progress of Scenario2 <u>Free expression and discussion</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 ± 6.62), 23 MCI (age = 77.6 ± 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 ^{†‡}	74.1 \pm 6.6	77.6 \pm 6.2	82. \pm 8
Level of Education, n (%)				
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 ^{*†‡}	28.4 \pm 1.1	25.5 \pm 2.1	22.67 \pm 3.6
FAB, mean \pm SD	14.25 \pm 2.7 ^{*‡}	16.3 \pm 1.1	14 \pm 2.4	12.33 \pm 3.1
FCSR Test	39.2 \pm 9.9 ^{*‡}	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 ^{†‡}	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

leo analyses data	MMSE	FAB	FCSR	NPI	IADL-E
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

	N	HC	MCI	AD	Activites completed (in mean \pmSD)
Good performance	22	13	9	-	10.04 \pm 1.4
Mediocre performance	16	1	10	5	5.5 \pm 1.2
Poor performance	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

Events	Recall	Precision
<i>Scenario 01</i>		
Mono Task	1	0.88
Dual Task	1	0.98
<i>Scenario 02</i>		
Searching Bus line	0.58	0.625
Medication preparation	0.87	0.93
Watering Plant	0.8	0.63
Reading Article	0.6	0.88
Preparing Drink	0.90	0.68
Talk on Phone	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>	Input Data		
<i>Performance</i>	Scenario 01	Scenario 02	Both Scenarios
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>	Input Data		
<i>Performance</i>	Scenario 01	Scenario 02	Both Scenarios
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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- 703
- 704 -

Figure 1.JPEG

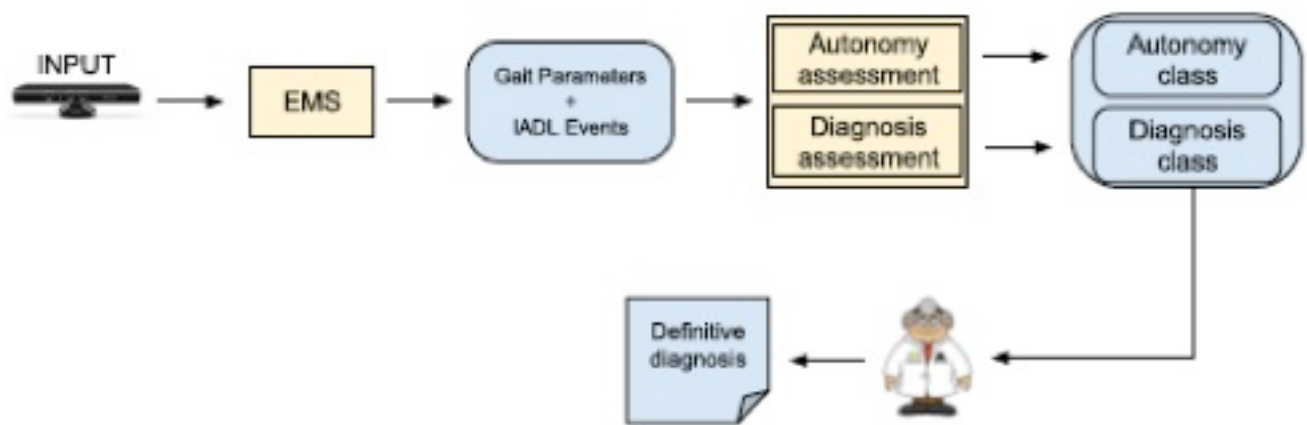


Figure 2.JPEG

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

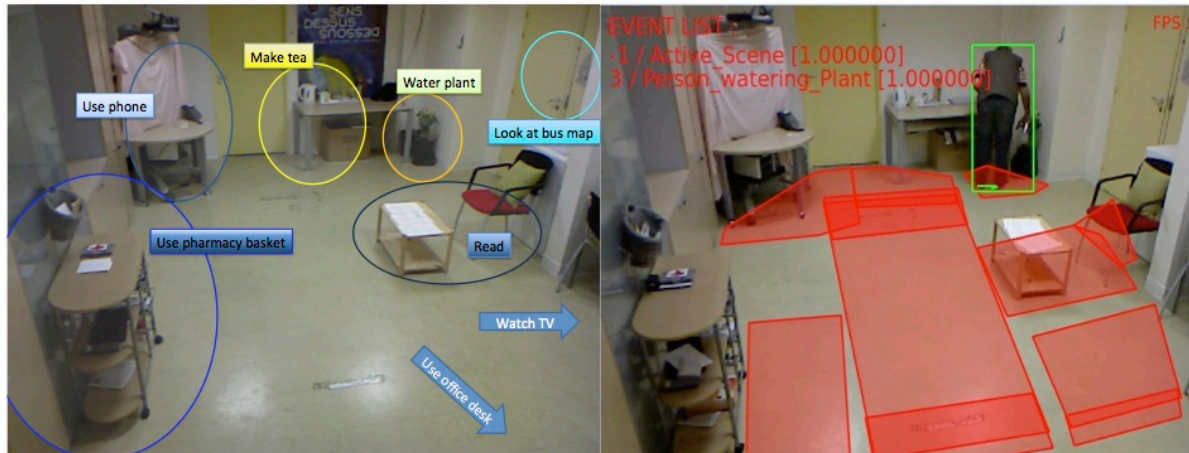


Figure 3. Event recognition based on Activity zones. The left image presents the contextual zones used to describe the scene semantics. The right image presents an example of output of the EMS system.

Figure 4.JPEG

