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i. Introduction

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

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

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

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

need for better measures of functional changes in people with the earliest changes associated with AD in clinicial trials (Snyder, 2014)
Besides, just a few of the named tools capture the earliest functional deficits seen in preclinical AD.

Growing recognition of the need for an more objective and direct measurement has led to some attempts to improve the assessments of IADL in clinical practice by developing new extensive informant-based computerized IADL questionnaire (Sikkes et al., 2012) or performance-based measures (Moore et al., 2007) which involve observing an individual enact an IADL, such as making a phone call or preparing his/her medications in either his natural or a clinical environment.
Farina et al. (2010) developed a new direct performance measure for patients with dementia, e.g. the functional living skills assessment (FLSA) (Farina et al., 2010). This tool was conceived to detect functional impairment targeting high-order social abilities in everyday-life and IADL by direct observation of the patient carrying out practical tasks or being verbally stimulated.

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

ICT and in particular automatic video analyses of patients carrying out various IADL could be an innovative assessment method (Robert et al., 2013) to help overcome those limitations in reducing the inter/intra-rater variability due to human interpretation and increase ecological value by removing completely the human observer from the assessment site. Such techniques enable the patients' performances and actions in real time and real life situations to be captured and accurately evaluated and could provide the clinician with objective performance measures and a « second opinion » regarding the overall state of functionality of the observed subject.

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

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

ii. Materials and Methods

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

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

Study participants and clinical assessment

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

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

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

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

Each participant underwent a standardized neuropsychological assessment with a psychologist. In addition, clinical and demographical information were collected. In order to accurately stage the participants cognitive status, global cognitive functioning was assessed using the MMSE (Mini Mental State Examination) (Folstein, 1975). Other cognitive functions were assessed with the Frontal assessment battery (FAB) (Dubois, 2000) and the Free and Cued Selective Reminding Test (Buschke, 1984; Grober, 1987). Neuropsychiatric symptoms were assed using the Neuropsychiatric Inventory (Cummings, 1997) and functional abilities were assessed using the IADL scale (IADL-E) (Lawton & Brody, 1969) during a clinical interview with the caregiver if there was one available.

Clinical protocol

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

The clinical protocol asked the participants to undertake first a set of physical tasks (Scenario 1) and secondly a set of typical IADLs (Scenario 2) followed by a free discussion period while being recorded by a set of sensors. Scenario 1 consisted of a single walking task and a dual task. The dual task involves walking while counting backwards from '305'. These tasks intend to assess kinematic parameters of the participant via gait analysis (e.g., duration, number of steps, cadence, stride length). Scenario 2, also called the 'ecological assessment of IADLs', consisted of carrying out a set of daily living activities such as preparing a pillbox or writing a check within a timeframe of 15 minutes (see Table 1.) followed by a short discussion. The defined activities were based on commonly used IADL questionnaires and represent at once activities with high or low cognitive demand (in accordance with the Bayer Activities of Daily Living scale) (Erzigkeit et al., 2001; Hindmarch et al., 1998). The protocol was conducted in an observation room located in the Nice Research Memory Center, which was equipped with everyday objects for use in ADLs and IADLs, eg, an armchair, a table, a tea corner, a television, a personal computer, and a library. RGBD sensors (Kinect ®, Microsoft ©) were installed to capture the activity of the participants during the assessment. The aim of this protocol is an ecological assessment based on a 'real time' performance, that determines to which extent the participant could undertake independently a list of daily activities within a timeframe of 15 minutes. All assessments were performed at the same time of the day, between 2 pm and 3 pm.

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

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

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

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	**Mono/Dual directed tasks** - Walking - Counting backwards - Both walking and counting backwards **Vocal directed tasks** - Sentence repeating task - Articulation control task	**List of ADLs/IADLs to organize and perform within 15mn** - 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	**Directed expression** Questions about tasks/progress of Scenario2 **Free expression and discussion** Verbal description of a picture Free discussion from the picture about the interest of the participant

CLINICAL TARGETS	• 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)

Data collection & Processing

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

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

Figure 1. System Architecture

Event Monitoring System

The event monitoring system is composed of four main modules: people detection, people tracking, gait analysis and event modeling. People detection step is performed by the background-subtraction algorithm proposed by Nghiem and Bremond (Nghiem, 2014). The set of people detected by this module is then tracked over the scene by the algorithm of Chau et al. (Chau, 2011). The output of these two modules is then used as input for gait analysis and event recognition. The latter module is based on the work of Crispim-Junior et al. (Crispim-Junior, 2013), where an constraint-based ontology language is employed to model daily living activities in terms of posture, motion and location of the participant in the scene. Figure 1 presents an example of event model for the recognition of Preparing Drink event. Briefly, an IADL event model is conditioned on the recognition of a set of event models that model one activity-related aspect each. For instance, the event model for "Prepare Drink" activity is based on the recognition of two sub-events (components): the person is where drinking objects are placed (named Person_in_zone_Drink) and the person exhibiting the posture "bending" (named Person_bending). Both components intervals also need to be recognized (happen) at the same time (c1->Interval AND c2->Interval). For more details on IADL event modeling, please refer to Crispim-Junior et al (Crispim-Junior, 2013). Figure 2 presents the definition of the explained event model following the ontology language.

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

Figure 2. Event model for Preparing Drink Activity

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.

Autonomy Assessment and Dementia Diagnosis Classification

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

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

Autonomy and Diagnosis Classes

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

Statistical analyses

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

iii. Results

Population

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

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

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

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 ST	77.7 ± 7.3†‡	74.1 ± 6.6	77.6 ± 6.2	82. ± 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 ± SD	25.6 ± 3.1*†‡	28.4 ± 1.1	25.5 ± 2.1	22.67 ± 3.6
FAB, mean ± SD	14.25 ± 2.7*‡	16.3 ± 1.1	14 ± 2.4	12.33 ± 3.1
FCSR Test	39.2 ± 9.9*‡	46.27 ± 1.9	38.19 ± 7.2	29.50 ± 16.7
IADL-E, mean ± SD	6.4 ± 1.3	7 ± 1.2	6.33 ± 1.7	6 ± 1.8
NPI total, mean ± SD	6.89 ± 8.1†‡	3.54 ± 2.8	5.77 ± 7.1	12.6 ± 11

Ecological assessment results

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

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

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

deo analyses data earman correlation coefficient (r) / p-values	**MMSE**	**FAB**	**FCSR**	**NPI**	**IADL-E**
tivities 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
tivities 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

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

Figure 4. Cumulative frequency curve of completed carried out activities

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

Table 4. Ecological Assessment results

	N	**HC**	**MCI**	**AD**	**Activites completed (in mean ±SD)**
Good performance	22	13	9	-	10.04 ± 1.4
Mediocre performance	16	1	10	5	5.5 ± 1.2
Poor performance	11	-	4	7	1.54 ± 1.4

Automatic video monitoring results

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

Table 5. Activity/Event Detection Performance

Events	Recall	Precision
Scenario 01		
Mono Task	1	0.88
Dual Task	1	0.98
Scenario 02		
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

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

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

Automatized classification of participant cognitive status

We compared the results for the percentage of patients correctly classified. For the three classifiers the data set is the same and contains 49 patients in total. The overall activities were correctly automatically detected with high sensitivity and precision results as previously described. Based on the automatically extracted behavioral data (see the list below), two different classifiers were learned: one for dementia diagnosis and the other for autonomy assessment (see Table 6).

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

In the Autonomy classification task the following features were employed:

- _ *Single Task Total Duration,*
- _ *Single Task Gap Duration,*
- _ *Single Task Standard Deviation Steps,*
- _ *Dual Task Gap Duration.*
- _ *Dual Task Max Steps,*
- _ *Person using PharmacyBasket Frequency of Event (frequency),*
- _ *Person using PharmacyBasket Duration of Event (seconds).*

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

- _ *Age,*
- _ *Single Task Average Steps,*
- _ *Single Task Speed Average from Centroid Information,*
- _ *Dual Task Max Steps,*
- _ *Dual Task Min Steps,*
- _ *Person reading inChairReadingTable Duration of Event (Frames),*

The classifier for Dementia Diagnosis task obtained an accuracy of 61.22% when using only features based on IADL (Scenario 2), and of 75.51% when just extracting features from Scenario 1, the physical tasks. The accuracy rate increased up to 73.46% when combining features from both scenarios. However, the higher recognition rates were found for the Classifier learned from the group of patients sorted by autonomy class; based on simply the automatically extracted video features from scenario 2, 77.55% accuracy was obtained and 75% accuracy for scenario 1. The highest accuracy rate of 83.67% was obtained when combining directed tasks and IADLs.

Table 6. Classification results

Autonomy assessment	**Input Data**		
Performance	**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%)

Diagnosis assessment	**Input Data**		
Performance	**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%)

iv. Discussion

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

The results demonstrate that all extracted elements of the clinical protocol, the kinetic parameters from the single and dual task, as well as the selected features from the IADL task, are important to take into consideration in the automatized analyses in order to assess and further predict accurately autonomy performance of patients. In fact, adding features from the very standardized directed tasks to the classification analyses even increased the accuracy rates for diagnosis but even more for the autonomy groups. This means that in extractable gait features such as 'Single Task Standard Deviation Steps' and 'Dual Task Gap Duration' lies relevant information about a patient's capacity to perform IADLs and therefore his or her autonomy level. These features added up to the automatically detected lengths and frequencies of the to carry out activities result in a highly accurate autonomy classification rate of almost 84%, allowing soon an almost fully automatized functional assessment in clinical practice. The work of Gillain et al. illustrates in the same manner that it may be possible to determine different cognitive profiles, and hence autonomy levels, by the measurement of gait parameters (Gillain, 2009). This confirms previous research findings that gait ability and cognitive functions are interrelated, and in particular executive functions and gait speed (Beauchet et al., 2013; Doi et al., 2013; Doi et al., 2014; Montero-Odasso et al., 2009). Gait impairment is already known to be a common characteristic of patients with MCI (Allan et al., 2005) and represents a risk factor for conversion to AD (Buracchio et al., 2010; Verghese et al., 2007). Therefore, changes in these motor function may be useful in the early detection of dementia during preclinical stages and easily measurable by sensor technologies.

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

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

The study's results were consistent with previous work where with a sensitivity of 85.31 % and a precision of 75.90% the overall activities were correctly automatically detected (Konig et al., 2015) although the present study was with a larger cohort and included as well AD patients.

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

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

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

Until now, the clinical assessment of functional changes in AD and MCI patients has traditionally relied on scales and questionnaires that are not always sensitive to the earliest functional changes. This leads to an important need to develop improved methods/techniques to measures these changes, ideally at the earliest stages. Therefore, recently research efforts have been placed on studies finding new innovative and more objective ways to measure functional and cognitive changes associated with AD (Goldberg et al., 2010; López-de-Ipiña, 2012; Vestal et al., 2006; Yakhia et al., 2014; Zola et al., 2013).

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

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

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

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

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

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

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

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

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

Conflict of Interest Statement

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

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Figure 1.JPEG

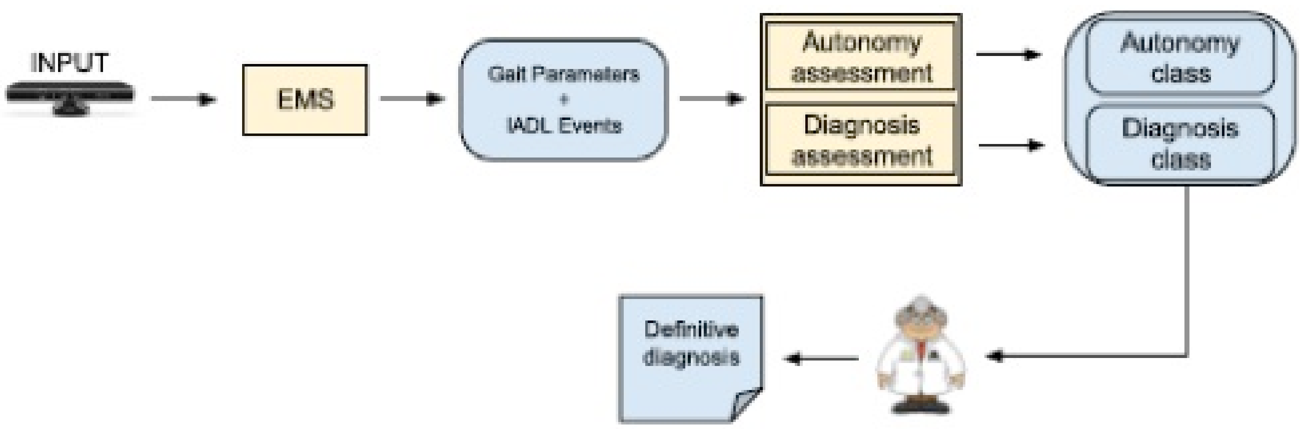

Figure 2.JPEG

```
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

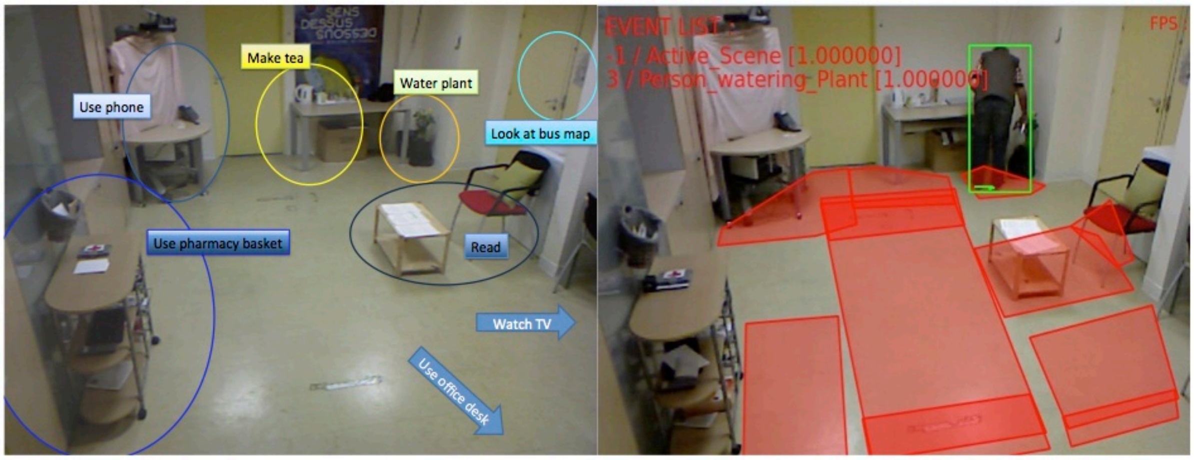

Figure 3. Event recognition based on Activity zones. The left image presents the contextual zones used to describe the scene semantics. The right image presents an example of output of the EMS system.

Figure 4.JPEG