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Multimodal Behavior Analysis Towards Detecting Mild Cognitive Impairment: Preliminary Results on Gait and Speech

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Abstract

Behavioral analysis for identifying changes in cognitive and physical functioning is expected to help detect dementia such as mild cognitive impairment (MCI) at an early stage. Speech and gait features have been especially recognized as behavioral biomarkers for dementia that possibly occur early in its course, including MCI. However, there are no studies investigating whether exploiting the combination of multimodal behavioral data could improve detection accuracy. In this study, we collected speech and gait behavioral data from Japanese seniors consisting of cognitively healthy adults and patients with MCI. Comparing the models using single modality behavioral data, we showed that the model using multimodal behavioral data could improve detection by up to 5.9%, achieving 82.4% accuracy (chance 55.9%). Our results suggest that the combination of multimodal behavioral features capturing different functional changes resulting from dementia might improve accuracy and help timely diagnosis at an early stage.

Keywords:

Alzheimer's disease, linguistic features, motion capture

Introduction

As the world's elderly population increases, the number of people living with dementia is rising rapidly, making dementia an increasingly serious health and social problem. According to a previous survey, around 47 million people globally were living with dementia as of 2015, corresponding to about 7.6% of the world's over-65-year-olds [1]. While dementia affects individuals within many domains, including cognition, neuropsychiatric symptoms, activities of daily living, and usually comorbid physical illnesses, it also affects their supporters, including relatives and even wider society because people with dementia require constant and costly care for years [2]. In fact, approximately 85% of the healthcare costs of dementia are related to family and society, and global annual costs reached over 818 billion USD in 2015 [2]. In contrast, there have been numerous attempts to develop an effective drug to combat dementia, but the results of trials have all been negative [2]. One of the remaining possible way to improve this situation is thought to intervene at earlier disease stages such as mild cognitive impairment (MCI) or preclinical Alzheimer's disease. Although there is no validated effective intervention, longitudinal studies suggested that early intervention at stage of MCI might reduce the progression to dementia [3]. An intervention that delays the onset of Alzheimer's disease (AD) dementia by 5 years is estimated to result in a 57% reduction in the number of AD patients and to reduce 45% of the projected Medicare costs [4]. Thus, early detection of dementia has been increasingly important. However, diagnostic coverage of dementia worldwide remains low, and even in high-income countries, only 40–50% of dementia sufferers have received a diagnosis [5,6]. Thus, detection at earlier disease stages should be a more challenging issue.

One of the most promising ways to detect dementia at early disease stages is identifying the evolution of behavioral change over the course of dementia's progression. Instead of medical examinations including brain imaging as well as in-clinic neuropsychological assessment, being capable of inferring dementia and MCI from behavioral features that can be measured in various everyday situations holds promise for increasing the opportunity for timely detection.

Among the behaviors, the most investigated might be speech and gait [7]. Speech has been used for characterizing language dysfunction resulting from cognitive changes [8-12]. For example, memory impairment causes difficulties with word-finding and word-retrieving, which has been measured by speech features such as fillers, including non-words and short phrases (e.g., "umm" or "uh") [9]. The reduction in speech expressiveness is another language dysfunction typically observed in both MCI and AD. This reduction is measured by the decrease in adjectives and indicators related to vocabulary richness (such as type-token ratio and Brunet's index) [10]. Gait disturbances are also common across the dementia spectrum, although the main clinical hallmark of dementia is cognitive impairment especially related to memory impairment [13]. Over the past decade, large cohort studies on dementia have shown the relationship between the severity of cognitive impairment and increased gait abnormalities [13-16]. For example, dementia is associated with a decrease in gait velocity and an increase in stride variability [17]. While there are limited studies evaluating gait in MCI, some but not all studies have suggested that gait dysfunction can be observed in patients with MCI even under normal walking conditions [13]. Although speech and gait features have been suggested as behavioral biomarkers for AD and possibly early in the course of dementia, including MCI, no studies have investigated whether combining both behavioral features could improve detection accuracy for MCI and AD. If speech and gait each could capture different aspects of subtle changes related to physical and cognitive functioning, the multimodal behavioral approach seems to be promising for building a model enabling detection at an earlier disease stage.

In this study, we investigate whether combining behavioral features of speech and gait could improve detection accuracy for patients with MCI. We collected speech and gait behavioral data from Japanese seniors consisting of cognitively healthy adults and patients with MCI. Specifically, speech data were collected while performing an picture description task by microphones, while gait performance was assessed during a 5-meter walk at normal speed by a marker-based motion capture system. Through the analyses, we demonstrate that exploiting the combination of multimodal behavioral data to identify MCI outperforms that based on each set of single-modality data alone by up to 5.9%, achieving 82.4% accuracy (chance 55.9%). The results demonstrate how our multimodal behavioral analysis could identify the early stages of dementia by exploiting the combination of subtle changes.

Methods

Participants

We collected data from 34 elderly individuals (20 females and 14 males, between 64 and 82 years, i.e., 73.06 ± 4.76). Nineteen participants were grouped as healthy controls (HCs) and fifteen as having MCI. There was no significant difference in age among the groups. Table 1 shows the number of participants (number of female participants), mean age, and mean Mini-Mental State Examination (MMSE) score for the HC and MCI groups. None of the participants in the HC group were diagnosed as having MCI or dementia before the experiment. The definitions of the MCI groups were based on diagnosis by psychiatrists through medical examinations including structural magnetic resonance imaging, blood tests, and neuropsychological tests. More specifically, the doctors followed the guidelines and criteria of the study by Petersen et al [18]. This study was conducted under the approval of the Ethics Committee, University of Tsukuba Hospital.

Speech data collection and feature extraction

We collected speech data from the participants while they performed the Cookie Theft picture description task. The Cookie Theft picture description task, adapted from the Boston Diagnostic Aphasia Examination, is a task used to test the production of free speech in a structured context [19]. A picture is provided to the participants, showing a mother and two children (a boy and girl). Participants are asked to tell everything they see in the picture. This task is used to test the ability of the participants to describe the characters and events in the scene.

The task was administered using a 2nd generation iPad Air through a web-based application using a Wizard of Oz experiment method. This method is efficient for examining user interaction with computers and facilitating rapid iterative development of dialog wording and logic. The method requires two machines linked together, one for the subject and one for the experimenter. In this implementation, the experimenter (the "Wizard"), pretending to be a computer, "operates" using complete replies to user queries or presses function keys to which common messages have been assigned. The software automatically records the dialog and its timing. This was done as a step towards a fully automated system to first assess the ability to achieve similar results using tablet devices as in traditional assessment styles.

Table 1 – Demographics of participants

Status	No. of Participants (Female)	Mean Age (SD)	Mean MMSE (SD)
Control	19 (12)	71.63 (4.39)	28.42 (1.47)
MCI	15 (8)	74.87 (4.73)	25.53 (3.89)

Voice recordings were collected using three microphones: a throat microphone (NANZU SH-12iK), a lavalier microphone (SONY ECM-CS3), and the iPad's internal microphone. The throat and lavalier microphones were fitted onto the participants' necks and connected to a USB recording device (ZOOM H1/MB) for voice recording (wav format, 44.1 k/stereo) (Figure 1A). Analysis was done on voice recordings gathered from the lavalier microphone, which were selected after synchronization with the throat microphone showing which portions of the recordings contained actual speech from participants. The throat microphone does not record the sound of open-air, so participants' speech area can be detected by extracting the sections above a certain volume level in the recorded audio. Recordings from the iPad's internal microphone were collected but not analyzed in this study. These recordings will be used in later analysis after the proper features have been selected and a model is developed from higher quality audio. After assessment, voice recordings from the lavalier microphone were used for preprocessing. The recorded audio was preprocessed by automatic speech recognition (ASR), which automatically transcribes audio data into text format. Then the experimenter manually corrected the errors of the ASR by listening to the recorded audio. The experimenter also annotated fillers and false starts during the transcribing procedure. For the preprocessing, we used the Japanese morphological analyzer MeCab [20].

Once all the transcribing and annotatince were completed, we collected speech features on the basis of the previous studies.

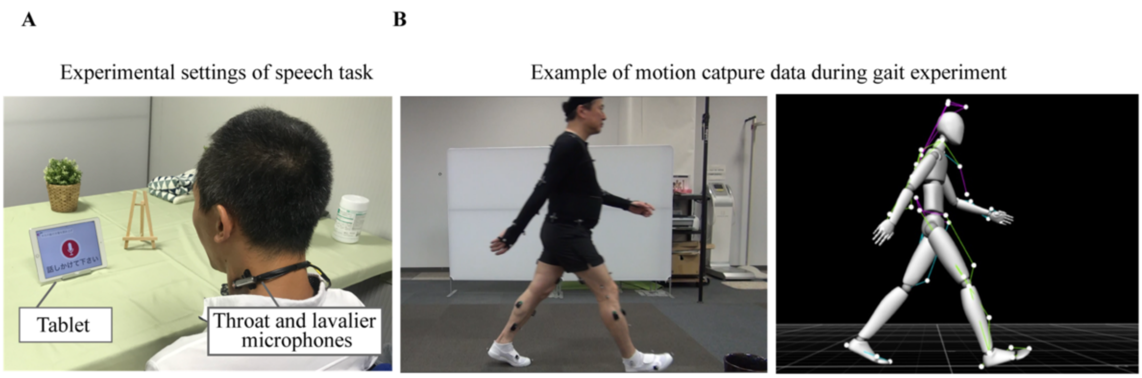

Figure 1 – Overview of speech and gait experiments. (A) Example of the speech experimental setup. (B) Example of motion capture data during gait experiment.

Previous study reported that syntactic complexity is closely associated with the incidence of dementia [21]. Syntactic complexity was measured in various ways, such as the mean length of sentences, number of sentences, "part-of-speech" frequency, and dependency distance [10,22]. Dependency distance infers the number of intervening words between two syntactically related words in a sentence [23]. Another feature that must be considered is vocabulary richness. This measures lexical diversity, which tends to reduce in dementia cases [9]. Repetitiveness is also reported as an important factor of capturing the linguistic dysfunctions of the patients with dementia [24]. Some matrixes measure the frequency of repeated words and phrases, and others estimate sentence similarities by calculating the cosine distance between two sentences [10]. The feature which widely used in image description tasks is semantic density. It was calculated on the basis of "informational units" that are predefined objects or text segments that might refer to important information. For example, in the Boston Cookie Theft picture description task, information units consist of objects such as "Woman", "Cookies", and "Boy taking the cookie". With the information units, semantic density can be defined as the number of information units divided by the total number of words [10,22]. A number of previous studies have found that individuals with dementia tend to produce speech with lower information, defined as semantic density, than with healthy controls [22, 25].

In this study, we collected 49 speech features from the transcribed and annoteated text of picture descrtion task. It includes twenty-seven features related to parts-of-speech (POS), four features related to information units (e.g. frequency, ratio), six features for syncatcic complexity (e.g. maximum dependency level), six different measures of sentence similarities (e.g. cosine-disntance), and three measures of vocabulary richness (e.g. type-token-ratio). Number of false starts and number of fillers are extracted from the annotation in the transcribed text. Addition to the text features, the speech rate (audio length/syllables) was also caluclated.

Gait data collection and feature extraction

The gait experiment was conducted on the same day as the speech experiment. The participants took enough rest between experiments. We collected motion data of the participants walking five meters in a lab area at their usual speed. To ensure that gait features were collected during steady-state walking, participants started walking at least two meters before the target zone and completed their walk at least two meters beyond it, which makes nine meters walk in total. Start and end points were marked on the floor with tape. Before each experiment, a trained experimenter gave verbal task instructions to the participants as "Please walk up to the tape at your usual speed".

Participants' body positions during their walk were captured by the motion capture system, OptiTrack Flex 13, with eight cameras allocated in a 6 meters × 12 meters walking area (Figure 1B). Three-dimensional kinematic data were measured at 120 Hz using a full body skeleton model of 50 markers. 50 markers includes head (4 markers), torso (6 markers), waist (4 markers), shoulder (4 markers), arm (6 markers), hand (8 markers), leg (8 markers), foot (6 markers), and toe (4 markers). Skeleton is calibrated for each participant before the gait experiment.

In a previous study, a broad range of characteristics is used to describe gait performance. Gait speed is applied widely as an evaluative and a predictive measure of various diseases [13,14,26]. Other measures such as gait velocity and stride variability has also been suggested as a sign of dementia [17]. Step width and step width variability reflect the postural control of gait [27].

In this study, we collected 13 gait features from the positional data obtained from each markers during a gait task. We calculated the gait cycle from four markers on each foot (toe in, toe out, toe tip, and heel). Once all the data preprocessing was completed, gait speed (walk length/time), step length (mean and standard deviation), stride (mean and standard deviation), left-right stride variability, toe angle (mean and standard deviation), left-right toe angle variability and step width (mean and standard deviation) were extracted from gait cycle. We also

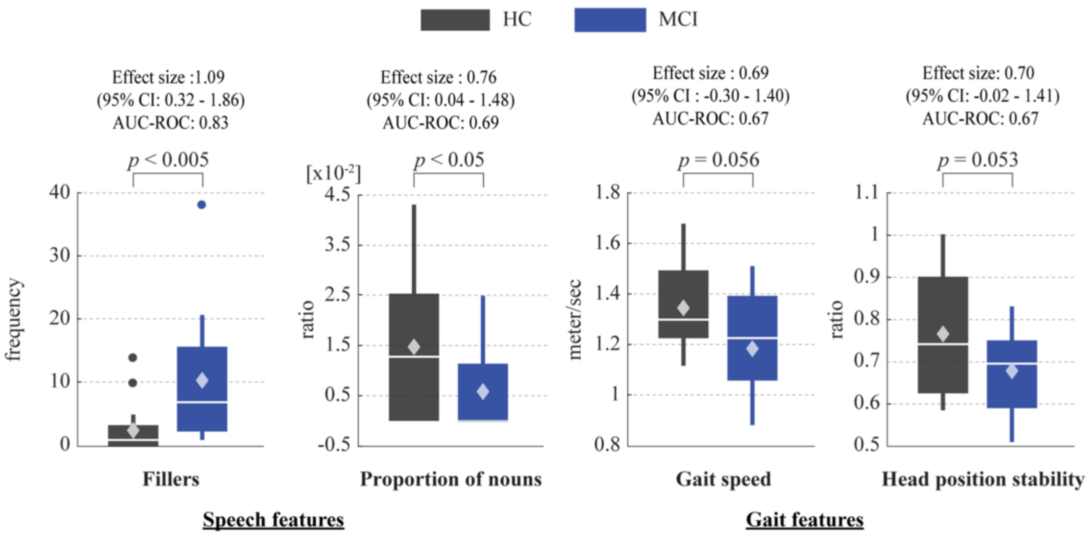

***Figure 2** – Distributions for speech and gait features which may have tendancy between HC and MCI groups. Boxes denote 25th (Q1) and 75th (Q3) percentiles. Line within box denotes 50th percentile, while whiskers denote upper and lower adjacent values that are most extreme within Q3+1.5(Q3-Q1) and Q1-1.5(Q3- Q1), respectively. Filled circles show outliers, and squares represent mean values.*

extracted the position of head top marker and calculated the variablity of the distance from the direction of travel to see the stability of the head position.

Feature anaysis & classification models

After linguistic features and gait features were extracted, we investigated if each feature differed significantly between the HC and MCI groups. We performed Student t-test for statistical examination, and considered to be significantly different when the p value was less than 0.05.

Classification was then done using support vector machine (SVM) models with a linear kernel function with a two-class classification model for testing the strength of features for differentiating patients with MCI from HCs in an automated fashion [28]. We used the algorithm for the SVM models implemented in MATLAB (MathWorks Inc., Natick, MA). Features were selected on the basis of the receiver operating characteristic (ROC) score for each feature.

We evaluated the model's accuracy by leave-one-out cross-validation, where classifers were trained using data collected from all participants expect one and then were tested on data of the one participant left out of the training data set. After obtaining loss estimate using cross-validation, accuracy, sensitivity, specificity and F-measure were calaulated for the model.

Results

We investigated if these features differed significantly between the HC and MCI groups for each task. Through the analysis, two features in speech, fillers and proportion of nouns showed siginificant difference between HC and MCI groups ($p < 0.005$ and $p < 0.05$, respectively; Figure 2). We calculated the effect size (Cohen's d) of each feature as discriminative power [29]. For Cohen's d, the 0.8 effect size is thought to be large, while the 0.5 effect is medium, and the 0.2 effect size is small [29]. We found large and medium effect size with fillers (effect size of 1.09, 95% CI: 0.32-1.86; Figure 2) and medium effect size with proportion of noun (effect size of 0.76, 95% CI: 0.04-1.48; Figure 2). For the gait features, gait speed and head postition stability were higher with HC than MCI, although this differences were not statistically significant (p=0.056 and p=0.053, respectively; Figure 2). These changes in the speech and gait features consistent with the results of previous studies that investigated the differnces in these measures with HC and dementia [10,13,22].

Next, we evaluated classification models for each speech and gait task between HC and MCI groups. As a result, for the speech features, three features were selected to be used for the classification model, which achieved 76.5% accuracy (sensitivity: 73.3%, specificity: 78.9%, F-measure: 0.733). As for gait features, three features were also selected for the classification model, which achieved 76.5% accuracy (sensitivity: 88.9%, specificity: 72.0%, F-measure: 0.667).

Finally, we analyzed the classification model by combining speech and gait features. We combined speech and gait features that were selected in each classification model. The accuracy was 82.4% (sensitivity: 76.5%, specificity: 88.2%, F-measure: 0.813) which improved by 5.9% from that of the classification models using the features of individual tasks.

Discussion

In contrast to previous studies focusing on detecting MCI and AD from a single modality of behavioral data, we aimed to argue the effectiveness of multimodal behavioral analysis. To this end, we collected and investigated speech data during the image description task and gait data during the 5-meter gait test with normal speed from cognitively healthy controls and MCIs.

Table 2 – Classification model performance for HC vs. MCI. Performance is measured after leave-one-out cross-validation (Acc: accuracy, Spe: specificity, Sen: sensitivity).

Features	Acc (%)	Spe (%)	Sen (%)	F-measure
MMSE (baseline)	76.5	72.0	88.9	0.667
Speech	76.5	78.9	73.3	0.733
Gait	76.5	72.0	88.9	0.667
Speech & Gait	82.4	88.2	76.5	0.813

We first investigated the significant differences of each feature and found significance only in speech features with a medium to large effect size. We did not find differences in gait features when comparing people with MCI to controls. Gait disturbance in MCI is still controversial [30], but a reason for the absence of significant differences can be explained by the following: gait patterns differ between MCI subtypes, and then the use of a heterogeneous MCI group, including people with single-domain and multi-domain MCI, increases the intra-group variability of gait features in MCI groups [31,32]. In our experiment, such a heterogeneous MCI group in addition to the small number of participants might be a possible reason. Therefore, we could not find features that differed significantly between the MCI and controls with a larger effect size in both sets of behavioral data.

We then built a classification model by combining these features. When we built models by using speech and gait data separately, the models each showed the same accuracy of 76.5%, which was the same accuracy of the baseline model by using MMSE scores. In comparison with these models, we showed that the model using multimodal behavioral data could improve detection by up to 5.9%, achieving 82.4% accuracy. The results indicate that exploiting the combination of multimodal behavioral data could improve the detection accuracy of MCI. Though no gait features differed significantly between the MCI and controls, these gait features could contribute to improving detection performance by combining speech features. These results might be made possible by exploiting the combination of multimodal behavioral features capturing different functional subtle changes resulting from MCI. If this hypothesis is true, our approach focusing on the multimodal behavioral analysis might be important especially (i) in targeting at earlier stages such as MCI or preclinical AD stages and (ii) in using data collected in non-controlled environments such as free living situations with a lot of noise.

One of the limitation in this study is the relatively small number of participants.. For future work, we will need to confirm our results on a larger number of participants. Another limitation is the limited number of task trials. The speech and gait data we analyzed were collected from a single trial from a single task. We need to conduct further research with data from multiple trials to verify our results.

To the best of our knowledge, this is the first empirical study to demonstrate that multimodal behavioral analysis on speech and gait data could improve detection accuracy for patients with MCI and might be useful for early detection of AD. We hope the results of our study will help promote future efforts towards timely diagnosis at an early stage such as MCI.

References

[1] M. J. Prince, M. Prina and M. Guerchet, World Alzheimer Report 2013: journey of caring: an analysis of long-term care for dementia. *Alzheimer's Disease International,* (2013).

[2] G. Livingston, A. Sommerlad, V. Orgeta, S. G. Costafreda, J. Huntley, *et al.,* Dementia prevention, intervention, and care. *The Lancet*, 390(10113) (2017), 2673-2734.

[3] T. Horr, B. Messinger-Rapport, and J. A. Pillai, Systematic review of strengths and limitations of randomized controlled trials for non-pharmacological interventions in mild cognitive impairment: focus on Alzheimer's disease. *J Nutr Health Aging 19*(2) (2015), 141-153.

[4] R. A. Sperling, P. S. Aisen, L. A Beckett, D. A. Bennett, *et al.*, Toward defining the preclinical stages of Alzheimer's disease: Recommendations from the National Institute on Aging-Alzheimer's Association workgroups on diagnostic guidelines for Alzheimer's disease. *Alzheimer's & dementia*, 7(3) (2011), 280-292.

[5] M. Prince, A. Comas-Herrera, M. Knapp, M. Guerchet, *et al.,*World Alzheimer report 2016: improving healthcare for people living with dementia: coverage, quality and costs now and in the future (2016).

[6] V. Kotagal, *et al*., Factors associated with cognitive evaluations in the United States. *Neurology* 81 (2015), 64–71.

[7] A. Alberdi, A. Aztiria, and A. Basarab, On the early diagnosis of Alzheimer's Disease from multimodal signals: A survey. *Artificial Intelligence in Medicine*, *71* (2016), 1-29.

[8] I. Hoffmann, D. Nemeth, C. D. Dye, M. Pákáski, *et al.,* Temporal parameters of spontaneous speech in Alzheimer's disease. *Int J Speech Lang Pathol*, 12(1) (2010), 29-34.

[9] C. I. Guinn and A. Habash, Language Analysis of Speakers with Dementia of the Alzheimer's Type. In *AAAI Fall Symposium: Artificial Intelligence for Gerontechnology* (2012), 8-13.

[10] K. C. Fraser, J. A. Meltzer, and F. Rudzicz, Linguistic features identify Alzheimer's disease in narrative speech. *J Alzheimers Dis 49*(2) (2016), 407-422.

[11] K. Shinkawa and Y. Yamada, Word Repetition in Separate Conversations for Detecting Dementia: A Preliminary Evaluation on Data of Regular Monitoring Service. *Summit Transl Bioinform* (2018), 206-215.

[12] K. Shinkawa and Y. Yamada, Topic Repetition in Conversations on Different Days as a Sign of Dementia. *Studies in health technology and informatics*, *247* (2018), 641-645.

[13] V. Valkanova and K.P. Ebmeier, What can gait tell us about dementia? Review of epidemiological and neuropsychological evidence. *Gait & posture*, 53 (2017), 215-223.

[14] L. M. Waite, D. A. Grayson, O. Piguet, H. Creasey, *et al.,* Gait slowing as a predictor of incident dementia: 6-year longitudinal data from the Sydney Older Persons Study. *J Neurol Sci*, *229* (2005), 89-93.

[15] L. M. Allan, C. G. Ballard, D. J. Burn, and R. A Kenny, Prevalence and severity of gait disorders in Alzheimer's and non-Alzheimer's dementias. *J Am Geriatr Soc*, *53*(10) (2005), 1681-1687.

[16] E. Scherder, L. Eggermont, J. Sergeant, and F. Boersma, Physical activity and cognition in Alzheimer's disease: relationship to vascular risk factors, executive functions and gait. *Rev Neurosci*, *18*(2) (2007), 149-158.

[17] M. B. van Iersel, W. Hoefsloot, M. Munneke, B. Bloem, *et al*., Systematic review of quantitative clinical gait analysis in patients with dementia. *Z Gerontol Geriatr*, *37*(1) (2004), 27-32.

[18] R. C. Petersen, G. E. Smith, S. C. Waring, R. J. Ivnik, et al., Aging, memory, and mild cognitive impairment. *International psychogeriatrics*, 9(S1) (1997), 65–69.

[19] E. Kaplan, The assessment of aphasia and related disorders (Vol. 2). *Lippincott Williams & Wilkins* (1983).

[20] T. Kudo, Mecab: Yet another part-of-speech and morphological analyzer. *http://mecab. sourceforge. net/* (2005).

[21] S. Kemper, M. Thompson, and J. Marquis, Longitudinal change in language production: Effects of aging and dementia on grammatical complexity and semantic content. *Psychol Aging* (2001), 600–614.

[22] S. Ahmed, A. M. F. Haigh, C. A. de Jager, and P. Garrard, Connected speech as a marker of disease progression in autopsy-proven Alzheimer's disease. *Brain*, 136(12) (2013), 3727-3737.

[23] S. Pakhomov, D. Chacon, M. Wicklund, and J. Gundel, Computerized assessment of syntactic complexity in Alzheimer's disease: A case study of Iris Murdoch's writing. *Behavior research methods*, *43*(1) (2011), 136-144.

[24] Tomoeda CK, Bayles KA, Trosset MW, Azuma T, and McGeagh A, Cross-sectional analysis of Alzheimer disease effects on oral discourse in a picture description task. *Alzheimer Dis Assoc Disord* 10 (1996), 204-215.

[25] B. Croisile, B. Ska, M. J. Brabant, A. Duchene, *et al.*, Comparative study of oral and written picture description in patients with Alzheimer's disease. *Brain Lang,* 53(1) (1996), 1–19.

[26] S. Lord, B. Galna, J. Verghese, S. Coleman, *et al.*, Independent domains of gait in older adults and associated motor and nonmotor attributes: validation of a factor analysis approach. *J Gerontol A Biol Sci Med Sci*, 68(7) (2012), 820-827.

[27] E. Nordin, R. Moe-Nilssen, A. Ramnemark, and L. Lundin-Olsson, Changes in step-width during dual-task walking predicts falls. *Gait & posture*, 32(1) (2010), 92-97.

[28] B. E. Boser, I. M. Guyon and V. N. Vapnik, A training algorithm for optimal margin classifiers. In *Proceedings of the fifth annual workshop on Computational learning theory, ACM* (1992), 144-152

[29] S. Nakagawa and I. C. Cuthill, Effect size, confidence interval and statistical significance: a practical guide for biologists. *Biological reviews*, 82(4) (2007), 591-605.

[30] A.F. Pettersson, E. Olsson, and L.O. Wahlund, Motor function in subjects with mild cognitive impairment and early Alzheimer's disease, *Dement Geriatr Cogn Dis,* 19 (5–6) (2005), 299–304.

[31] M. Montero-Odasso, A. Oteng-Amoako, M. Speechley, K. Gopaul, *et al.,* The motor signature of mild cognitive impairment: results from the gait and brain study, *J Gerontol A Biol Sci Med Sci,* 69 (11) (2014), 1415–1421.

[32] J. Verghese, M. Robbins, R. Holtzer, M. Zimmerman, *et al.,* Gait dysfunction in mild cognitive impairment syndromes, *J Am Geriatr Soc*, 56 (7) (2008), 1244–1251

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