DOI: 10.1016/j.jalz.2019.08.193

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FEATURED ARTICLE

Automated sensor-based detection of challenging behaviors in advanced stages of dementia in nursing homes

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Funding information
BMBF, Grant/Award Number: 16SV7348K

The authors have declared that no conflict of interest exists.

Abstract

Introduction: Sensor-based assessment of challenging behaviors in dementia may be useful to support caregivers. Here, we investigated accelerometry as tool for identification and prediction of challenging behaviors.

Methods: We set up a complex data recording study in two nursing homes with 17 persons in advanced stages of dementia. Study included four-week observation of behaviors. In parallel, subjects wore sensors 24 h/7 d. Participants underwent neuropsychological assessment including MiniMental State Examination and Cohen-Mansfield Agitation Inventory.

Results: We calculated the accelerometric motion score (AMS) from accelerometers. The AMS was associated with several types of agitated behaviors and could predict subject's Cohen-Mansfield Agitation Inventory values. Beyond the mechanistic association between AMS and behavior on the group level, the AMS provided an added value for prediction of behaviors on an individual level.

Discussion: We confirm that accelerometry can provide relevant information about challenging behaviors. We extended previous studies by differentiating various types of agitated behaviors and applying long-term measurements in a real-world setting.

KEYWORDS

Accelerometry, Challenging behavior, Dementia, Nursing home, Real-world evidence

1 | INTRODUCTION

The large majority of persons with dementia (PwD) exhibit behavioral and psychological symptoms such as agitation, apathy, aggression, sleep problems, or wandering during the course of their disease.[1] These symptoms lead to extensive burden for caregivers and are the main drivers of early institutionalization of patients.[2–4] Several tools and questionnaires have been developed, such as the Cohen-Mansfield Agitation Inventory (CMAI), Neuropsychiatric Inventory, or Behavioral Pathology in Alzheimer's Disease Rating Scale, to assess the degree and pattern of challenging behaviors in individual patients.[5–7] Although the reliability of these tools is appropriate, they suffer from some drawbacks. They are applied retrospectively and rely on the judgment of an informed caregiver. The subjective evaluation is dependent on the memory of the caregiver and the time spent with the PwD.[8] So a novel approach of the last years was the development of an observer-independent method to capture behavioral disturbances by sensors. A widely used method is to equip PwD with wearable accelerometers to monitor their activity continuously without restraining their natural movements and interfering with the behavior to be observed. Currently, several studies are available from different settings that evaluated the detection of challenging behaviors in PwD using sensors.[8–12] These studies suggested that actigraphy can serve as an objective tool for the assessment of behavioral symptoms in PwD. However, with a single exception,[10] all previous studies used retrospectively employed assessment scales as reference standard for the sensor-based assessment.

Here, we extended the scope of these previous studies by determining the predictive value of actimetric movement features for challenging behaviors by using both retrospective assessment scales and long-term (4 weeks) real-time and video-based behavioral annotations as references. We previously have introduced the framework of our study with multidimensional assessment of challenging behaviors via complex sensors, real-time observation, and video recording in people with advanced stages of dementia living in nursing homes.[13] Here, we present the results of the data analysis. As index test, we used the accelerometric motion score (AMS) derived from the raw sensor data that had been found a sensitive predictor of agitated behavior in a previous study in an independent cohort of PwD.[14] Our aim was to investigate the relationship between the AMS index test and the CMAI as well as the online and video-based behavioral annotations as reference tests. Sensor-based detection of behavioral symptoms in people with dementia offers the potential for individually tailored interventions that integrate the cognitive and health status of a person, the knowledge about personal traits and the current situation. In the longer run, such methods could help to improve dementia care, avoid use of psychotropic medication with its limited effectiveness and high rates of side effects,[15] and reduce caregiver burden, e.g. by revealing trigger factors for certain behaviors[15] or integrating alarm functions.

RESEARCH IN CONTEXT

1. Systematic review: We reviewed literature using medical databases like PubMed, conference abstracts, and cited work in review articles. Numerous studies examined challenging behaviors in persons with dementia (PwD) and accelerometry. Only few studies used direct observation of behavior for validation of accelerometric data.
2. Interpretation: Our findings confirm that behavior of PwD can be observed via accelerometry with longterm recordings. Accelerometric data could provide added value for prediction of behaviors. It is challenging to detect different types of behavior instantaneously even with extensive monitoring of resident's behavior in real time parallel to sensor mounting.
3. Future directions: We plan to enhance possible use cases for accelerometry. On one hand, we support caregivers by visualizing activity data, so that it is intuitively understandable but contains adequate preciseness for monitoring behavior of PwD and evaluate the effect of certain interventions. On the other hand, we will examine the possibility to detect disorientation with accelerometry for implementing in assistive technologies for supporting PwD.

2 | SUBJECTS AND METHODS

2.1 | Subjects

In the present study, 17 residents (11 women/six men) with moderate to severe stages of dementia, living in two different nursing homes, underwent multimodal sensor assessment together with real-time observation of their behavior over 4 weeks. In addition, the behavior of eight residents in one nursing home was also captured with videotaping over 4 weeks. Detailed information about the design of this project can be found in the publication by Teipel et al.[13] The PwD were recruited from two specialized dementia care units of two nursing homes of the "Krefelder Stadtische Seniorenheime", Krefeld, Germany. The age of subjects ranged from 73 to 94 years. All of them had been under psychopharmacologic treatment during the study. In particular, atypical antipsychotics were given to 12 subjects, antidepressants to 11, low-potential antipsychotics to six, nonbenzodiazepine hypnotics to five, and benzodiazepines to one. Antidementia drugs were taken by eight participants. In addition to the PwD, the holders of their durable power of attorney gave written informed consent for the participation in the study because, except of one, none of the PwD were able to give informed consent. Because behavior of residents was also observed in common-used rooms such as the sitting room, the written informed consent of all staff members, regular visitors, and also the holders of the durable power of attorney of the residents who were not participants of the study have been obtained before the videotaping started. The study was approved by the institutional review board of the German Society of Nursing Science (No. 16-007).

2.2 | Neuropsychological assessment

Because all residents were in advanced stages of dementia, extensive neuropsychological testing was not possible. The measurement of cognitive status was restricted to the Mini-Mental State Examination[17] and the Global Deterioration Scale.[18] The median Mini-Mental State Examination was eight points, ranging from five to 18 points, where the Mini-Mental State Examination could not be obtained in nine subjects who were either too severely impaired ($n = 5$) or refused testing ($n = 4$). For assessment of challenging behaviors, we used the Neuropsychiatric Inventory[6] and the CMAI[5] that were conducted with nurse staff of the care units as proxies. The CMAI includes 29 items that had to be rated on a Likert scale from one to seven. To detect depressive symptoms, the nurse staff were also asked to rate the mood of residents on a scale from one to eight, referring to the test for early diagnosis of dementia with differentiation from depression.[19] The diagnosis of dementia and the classification according to the International Classification of Diseases 10th edition was made by neurologists in 15 of the residents. Two residents were diagnosed by a general practitioner.

2.3 | Annotation of behavior

The behaviors of the residents of two nursing homes had been rated in real-time between April and July 2016 using a self-developed annotation scheme. The operationalization was based on dementia care mapping[20] while the definition of the challenging behaviors to be observed was based on literature research. Details can be found in the publication by Teipel et al.[13] The aim was to assess the behavior of PwD that is relevant for care in a nursing home setting and potentially detectable with sensors. The developed annotation scheme contained the following seven classes of behavior: aggression, apathy, general restlessness, performing repetitious mannerisms, trying to get to a different place, pacing, and other. Other behavior was defined as other than challenging behavior. In summary, annotations were done by 11 different observers who have been qualified dementia care mapping raters or trained study nurses. Annotations were done every five minutes in the morning between 9:00 AM and 1:30 PM and in the afternoon between 3:00 PM and 7:00 PM using paper and pencil annotation. If more than one class of behavior was observed during a 5-minute interval, all observed classes of behavior were annotated. To ensure the privacy of PwD, times of personal hygiene were not accompanied. The observation period per subject was between 24 and 28 days in a row.

2.4 | Videotaping of behavior

Video observation was obtained only in the common rooms and the hallway of one of the two nursing homes, including eight subjects, over a period of 4 weeks from 9:00 AM to 1:30 PM and 3:00 PM to 7:00 PM. One family caregiver in the other nursing home did not agree with obtaining video so that videotaping was done only in one of the two nursing homes. A network-attached storage system with a built-in video surveillance solution was used to store the data. The recording could be paused at all times with a remote control that was handed out to the nurses. Overall, we recorded 1.6 TB of video from four different cameras. Video observation was performed from trained students of social sciences using the ELAN software (ELAN Linguistic Annotator 4.9.4.; Max Planck Institute for Psycholinguistics Nijmegen, The Netherlands).

2.5 | Sensor mounting and data management

Details of the sensor data processing and derivation of the AMS can be found in Supplementary Material.

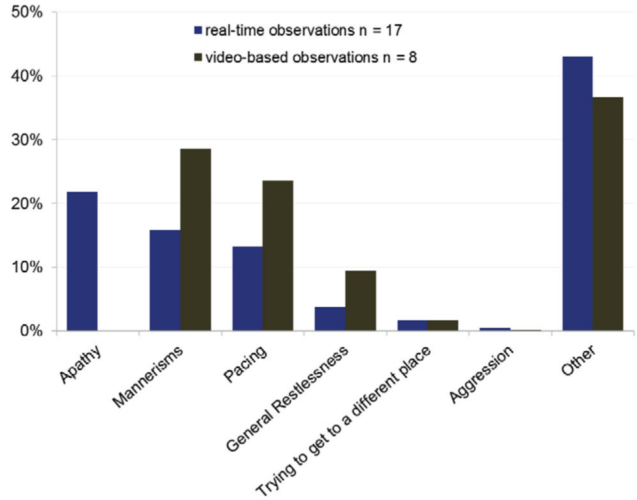

FIGURE 1 Distribution of observed behavior over the different classes of behavior. Comparison of real-time and video-based observations.

2.6 | Data analysis

We used the R environment (R for Windows 3.4.4. and R Studio®, Version 1.1.442; RStudio Inc., Boston, USA) for statistical analysis. For testing of correlation of AMS and CMAI, we used the Pearson product moment correlation for normally distributed variables. To check for normality, we used the Shapiro-Wilk normality test. A P value above .05 in the Shapiro-Wilk test was considered to be consistent with a normal distribution. For all other variables, we performed the Spearman rank-order correlation. To check for the relationship between the AMS and the observed behavior, we used a Dirichlet regression model for compositional data,[21,22] implemented in the R-package "DirichletReg." We chose a significance level of .05 with a corresponding confidence level of 95%. When we applied t-tests, we previously checked for equality of variances with the F-test. For unequal variances, we performed Welch's t-test. Every t-test was performed two-tailed. For testing the interobserver reliability, we calculated Cohen's kappa for both real-time annotations and video-based annotations. Based on the relative proportion of the agitated behavior, we used the k-means cluster algorithm to group the subjects into k = 2 groups. Owing to the relative small number of participants, a greater number of k would not be reasonable. To perform a linear discriminant analysis with leave-one-out cross-validation for the prediction of the behavior, we used the "MASS"-R-library.

3 | RESULTS

3.1 | Occurrence of challenging behavior

The frequencies of observed challenging behaviors from the real-time observations and the videotaping are reported in Fig. 1. Of note, because apathy could not reliably be discriminated from sleeping or

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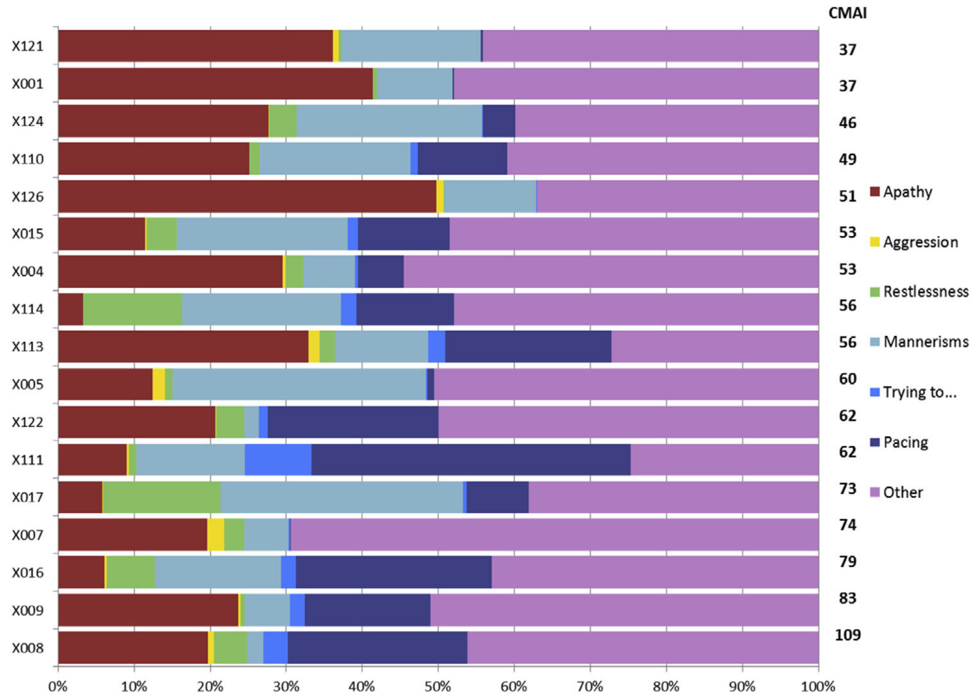

FIGURE 2 Proportions of observed behavior for each subject, sorted by the total CMAI in ascending order. Abbreviation: CMAI, Cohen-Mansfield Agitation Inventory.

resting in videoanalysis, apathy was excluded from the annotation scheme for the videotaping. The annotation scheme for real-time observations still contained seven classes. The frequency of observed challenging behaviors in the videotaping showed the same relative proportion of frequencies as the real-time observation.

3.2 | CMAI and directly observed behavior

The CMAI that was administered after the end of the observation period was used in the following analysis as reference test. The total CMAI score of agitated behaviors ranged from 37 to 109 within subjects and was further subdivided into the groups "physical" (21 items) and "verbal" (eight items). Each group was again divided into "aggressive" and "nonaggressive" items referring to Cohen- Mansfield.[23] The relative portion of each behavior class based on the real-time observed behavior for every resident is shown in Fig. 2. The **total CMAI** score showed a significantly negative association with the behavioral class "apa- thy$_{live}$" (P value < .05). When divided into the subitems, the **CMAI score of physical agitated behavior** showed a significantly negative association with apathy$_{live}$ (P value = .006) and mannerisms$_{live}$ (P value = .041) and a positive association with pacing$_{live}$ (P value = .033). The **CMAI score of physical nonaggressive behavior** showed a negative association with apathylive (P value = .002) and a positive association with pacing$_{live}$ (P value < .001; Fig. 3). When considering the association between the **CMAI score of physical aggressive behavior** and observed behaviors, all behavior categories except "mannerisms$_{live}$" showed a positive significant association with the CMAI score (P value < .05). In contrast, the **CMAI scores of verbal agitated behaviors**, including the subitems "**verbal aggressive**" and "**verbal nonaggressive**," did not show any significant associations with any behavior class.

In video data, the **CMAI score for physical agitated** items was significantly positive associated with pacing$_{video}$, but not with apathy$_{video}$ or mannerisms$_{video}$. **Physical nonaggressive CMAI** items showed no significant association, whereas the score of **physical aggressive items** was positively associated with mannerisms$_{video}$ (P value = .02), pacing$_{video}$ (P value = .03), and other$_{video}$ (P value = .03). Aggression was not significantly associated with this CMAI subgroup, different to the real-time observations. Also concordant to the real-time observations, neither the sum of all **verbal agitated items** nor the subgroups **verbal aggressive** and **verbal nonaggressive** showed a significant association to any behavior$_{video}$.

3.3 | AMS and CMAI

Both the aggregated AMS of the right foot (AMS$_{r}$j$_{ght\ foot}$) and the dominant hand (AMS$_{dominant\ hand}$) were significantly correlated with the total CMAI score (Spearman rho = 0.60 and 0.49, respectively, P value < .05 for both comparisons) and with the subgroups CMAI physical (Spearman rho = 0.82 and 0.66, P value < .01, respectively, Fig. 4) and CMAI physical nonaggressive (Spearman rho = 0.86 and 0.65, P value < .01, respectively). The CMAI verbal score and verbal subgroup scores, as well as the score for the CMAI physical aggressive subgroup, showed no significant correlation with any AMS.

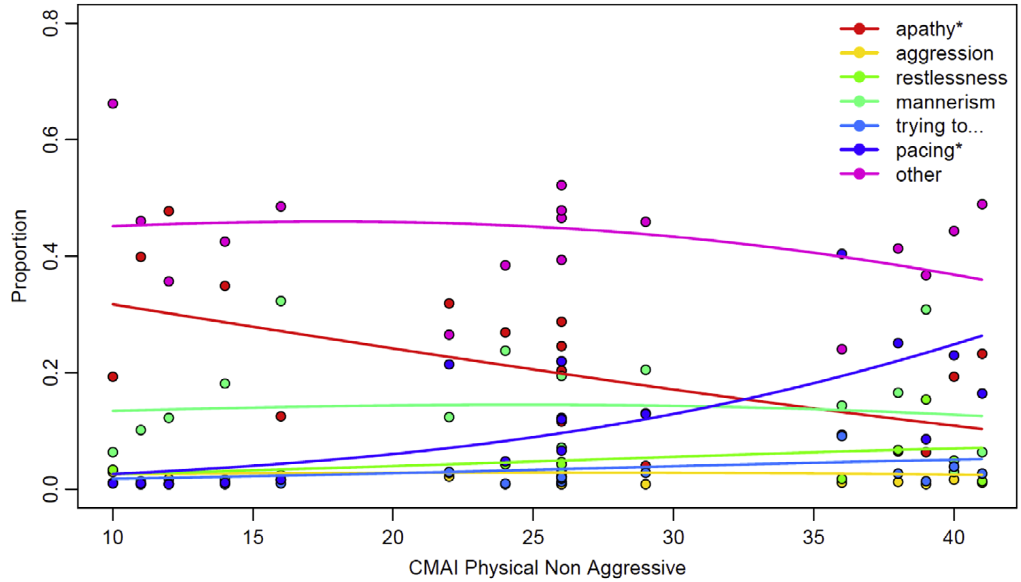

FIGURE 3 Distribution of observed behavior proportions related to the CMAI score for physical nonaggressive items. Lines show the regression (Dirichlet regression) for each behavior class. Apathy is negatively associated with increasing CMAI, whereas pacing is positively associated. All other behaviors are not significantly associated with the CMAI score. * indicates significant results. Abbreviation: CMAI, Cohen-Mansfield Agitation Inventory.

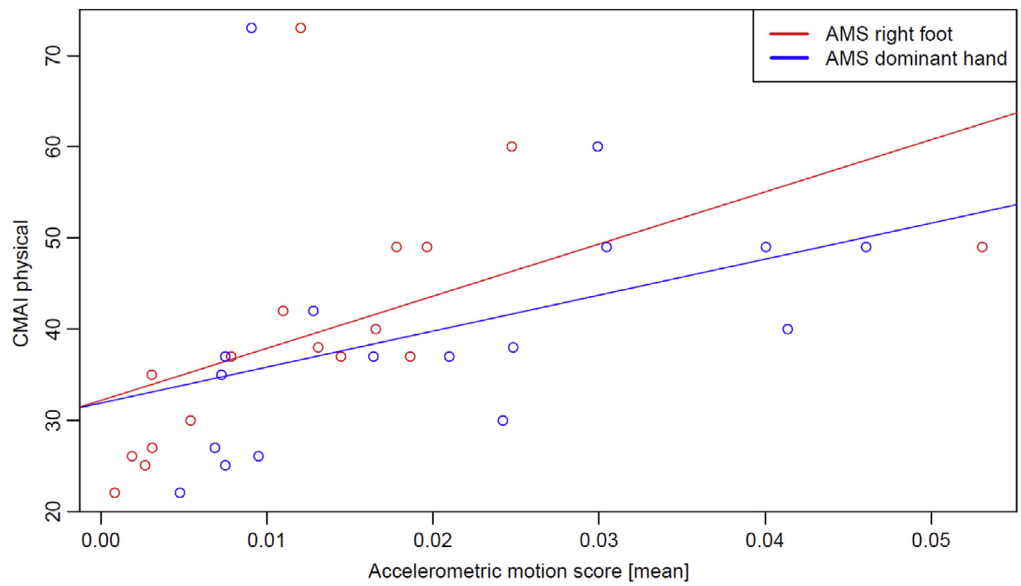

FIGURE 4 Correlation of the AMS of right foot and AMS of dominant hand with the CMAI score for physical items. Abbreviations: AMS, accelerometric motion score; CMAI, Cohen-Mansfield Agitation Inventory.

3.4 | AMS and directly observed behavior

At first, we checked the real-time observed behaviors for an association with AMS. As expected, the $AMS_{right\ foot}$ showed a positive association with $pacing_{live}$ (P value = .030) (Fig. 5). The AMSdominant hand was negatively associated with $apathy_{live}$ but positively with $mannerisms_{live}$ and $pacing_{live}$ (P value < .05). When performing the analyses with the observed behavior from videotaping, the $AMS_{right\ foot}$ was associated with every behavior. The $AMS_{dominant\ hand}$ did not show a significant association with any behavior. Because one of the subjects had extraordinary high AMS_{right} foot values, it was considered as potential outlier. After removing it from the sample, the positive association with pacing was still significant in the real-time observations. In the video-based observations, there were no longer any significant associations.

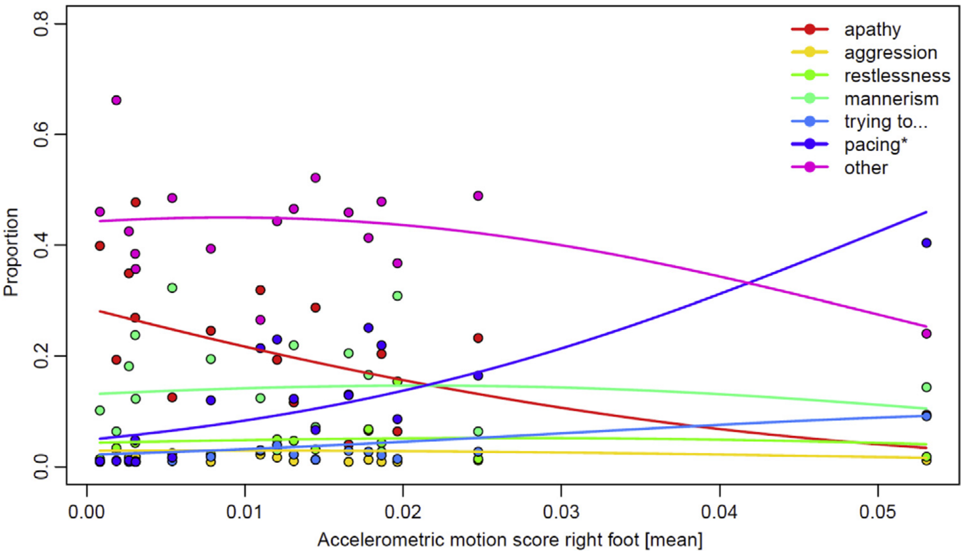

FIGURE 5 Dirichlet regression of AMS right foot and behavior. Pacing and AMS are positively associated. * indicates significant results. Abbreviation: AMS, accelerometric motion score.

3.5 | Influence of gender and age

To check for the sensitivity of our findings to the effects of age or gender, we repeated the Dirichlet regressions between AMS scores and behavioral observations with age and gender added as fixed effects to the models. When adding age and gender to the regression models, the $AMS_{right\ foot}$ now showed a significant (positive) association with all behaviors and the $AMS_{dominant\ hand}$ was not only significantly associated with mannerisms and pacing but also with general restlessness and the behavior of trying to get to a different place. The Dirichlet regression from AMS and video-based behavior with the variables age and gender did not converge because of the low number of remaining degrees of freedom.

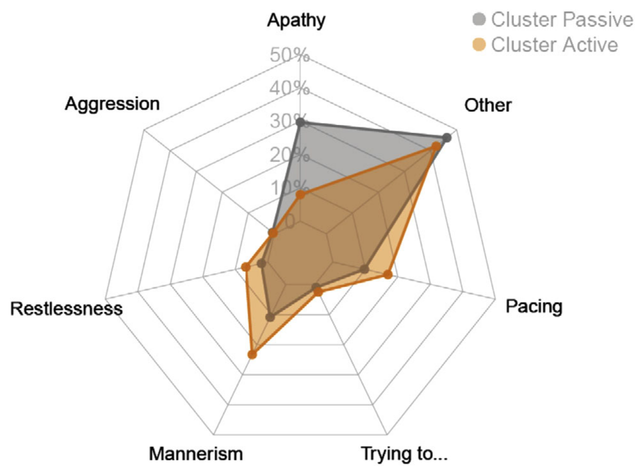

FIGURE 6 Spider-plot of both clusters of behavioral types; dots mark the mean proportion of each behavior. The group with more active features of challenging behaviors (n = 11) is colored in orange, and the group with more passive features of challenging behaviors (n = 6) is colored in gray.

3.6 | Interrater reliability of annotations

To evaluate the inter-rater agreement of real-time annotations, we calculated Cohen's kappa with the result of a low to moderate reliability for the 5-minute real-time annotations ($\kappa = 0.45$). The behavioral annotations reached a high reliability in the video-based ratings (pacing: $\kappa = 0.84$, mannerisms: $\kappa = 0.75$).

3.7 | Evaluation of the AMS for identification of behavior

We clustered the residents on the basis of their real-time annotated behavior into two groups using k-means clustering. The number of two clusters had been decided a priori given the small number of available cases. We found a group that contained residents with more passive features of challenging behaviors (n = 6), which showed more apathy and less frequent restlessness, mannerisms, and pacing ("Cluster P"). The second group ("Cluster A") comprised residents with more active features of challenging behaviors (n = 11; see Fig. 6). Subsequently, we used linear discriminant analysis to classify individual group membership of each patient based on the AMS and demographic predictors. Accuracy was determined using leave-one-out cross-validation. Using only the $AMS_{right\ foot}$ for the group classification reached an accuracy of 76.5% (13 of 17 residents were classified correctly). When we added age and gender as variables to this model, the accuracy of group classification dropped to 70.6%. Age and gender alone yielded an accuracy level of 70.6% as well. The $AMS_{dominant\ hand}$ alone yielded an accuracy of 88.2% (15 of 17). Adding age and gender to the model did not change this level of group classification accuracy. A clustering with the video-based behavior would have been inadequate because of the small number of subjects in this group.

4 | DISCUSSION

We investigated the automated detection of challenging behaviors in people with advanced stages of dementia living in nursing homes using long-term accelerometric recordings.

The total CMAI score and the CMAI score of physical agitated behaviors showed a significantly negative association with the degree of prospectively assessed apathy. The 29-item CMAI does not include apathy as an item; however, higher degree of actively challenging behavior in the prospective data was associated with lower degree of apathy, consistent with the inverse association of CMAI-rated agitation and the observation of apathy. The absence of an association between CMAI verbal agitated behaviors and any of our observed behaviors is consistent with our definitions of the behavioral classes because they did not include verbal behaviors. As a note of caution, the range of the CMAI scores in the domain of physical aggressive behavior was low, so that the comprehensive association of these CMAI ratings with all prospective behavioral ratings, except mannerisms, may have resulted from an overfitting of the model. Together, these findings support the construct validity of the prospective ratings in respect to agitated behavior categories.

The AMS from foot and hand was significantly positively associated with pacing and negatively associated with apathy (AMS_{foot}), consistent with a previously found high degree of association between AMS and agitated behavior in an independent cohort[14] and previously reported associations between actimetry and retrospective apathy ratings[8,11,24] and pacing.[25–27] In our study, the AMS_{hand} was positively associated with mannerisms, defined as episodes of repetitive and sustained stereotypical movements of self-stimulation, such as tapping, taping, or rocking.[28] The association with AMS_{hand}, but not AMS_{foot}, agrees with the dominance of manual movements in this category of behavior. The prospective observation of agitated behavior in PwD in real time in synchrony with acceleromet- ric signals was used in only few previous studies.[10,26] Bankole et al. 2012[10] could differentiate agitated and nonagitated (preagitation and postagitation episodes) behavior on the basis of accelerometric motion data. They did not define agitated behavior and did not specify the activities. Algase et al. 2003[26] only focused on the relation of wandering behavior and actigraphy.

When we tested for a correlation of the AMS with the CMAI, the AMS was positively correlated with the sum of the CMAI physical items, but not the CMAI sum of the verbal items. This underlines the specificity of the association between prospectively measured motion activity and retrospectively assessed behavior. Similar results had been reported before with a positive association of accelerometric scores with total CMAI score.[9,10,29] Our findings on the CMAI subclasses partly agree with one previous study that found a positive correlation with the CMAI score of physical nonaggressive behavior but also with verbal agitated behavior[29] and fully agree with one study that found no significant correlation of accelerometric measures with the CMAI score of verbal agitated behavior.[9]

Finally, we wanted to check if the AMS provides an added value for the classification of behavior on an individual level. To this end, we classified the subject sample into two groups using unsupervised clustering in the first step and tested the accuracy for group classification in the second step based on the AMS and demographic predictors, using leave-one-out cross-validation. The resulting groups differed in the occurrence of active and passive features of challenging behaviors (apathy, restlessness, mannerisms and pacing). They did not show a significant difference in the amount of other (normal) behavior. Without AMS, using only the variables age and gender, the accuracy of the group classification was 12 of 17. Using the AMS alone led to the correct classification of 13 ($AMS_{right\ foot}$) and 15 ($AMS_{dominant\ hand}$) residents, which was not further improved by adding age or gender. Even these numbers provide a first estimate of the potential effect-size of the AMS, this approach does not allow the classification of distinct behaviors nor the differentiation between agitated and nonagitated behaviors. Further studies in an independent sample are required to tackle that issue.

Owing to the complex setup of our experiments in the routine care setting of nursing homes, the number of cases we could recruit was limited with 17 cases for the prospective annotation. Only a subsample of eight cases had been videotaped. The observation period of 4 weeks was long in comparison to previous studies,[30,31] eventually leading to stable estimates of aggregated patient behavioral features. However, the prospective real-time assessment of behavior was challenging. Lacking generally accepted definitions for all the included behaviors (e.g. for restlessness), we referred for our annotation scheme to the dementia care mapping,[32] which has a very thoroughly developed codebook that, however, was not primarily developed for research applications. In addition, in a given time interval of 5 minutes, some residents did not only show one behavior but showed overlapping symptoms, as described by other reports before.[33–35] This leaves space for ambiguity despite a well-defined codebook for the behaviors and rater training. Still, given the large number of observations over the course of four weeks, such ambiguities would be expected to be attenuated when aggregating across the entire time period within each patient. Indeed, the aggregated ratings showed high replicability between different raters, much higher than the real-time observations for each 5- minute segment.[13]

In conclusion, we collected a comprehensive data set on resident's behavior and activity over a long observation period from a nursing home setting. Extending previous studies, we were able to assess the usefulness of accelero- metric measurements in reference to prospectively annotated behaviors. Beyond the mechanistic association between AMS and behavior on the group level, the AMS provided added value for the prediction of behaviors on an individual level. In an attempt to close a previously identified research gap,[36] we conducted the testing of the sensor system in a real-world setting, leading to methodological and ethical challenges that we have discussed before when describing the setup of the study.[13] The agreement of retrospectively and prospectively observed behaviors together with the coherence of accelerometric data with observed behavior is suggesting that the AMS may usefully complement current gold standard of retrospective ratings by objective assessment of PwD's behavior. This opens the perspective to use such measures to evaluate the effect of different interventions,[37] following the notion of the use of sensor-based assessments as real-world evidence of behavioral outcomes.[38] A future step will be the testing of automatic detection of instantaneous episodes of challenging behaviors, such as pacing, in real time. This will require classification algorithms to be trained on shorter episodes of synchronized sensor and observation data.

ACKNOWLEDGMENTS

The study was supported by a grant from the Federal Ministry of Research (BMBF) [grant 16SV7348K]. The funding agency did not play any active role in the scientific investigation and reporting of the study.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Goerss D, Hein A, Bader S, et al. Automated sensor-based detection of challenging behaviors in advanced stages of dementia in nursing homes. *Alzheimer's Dement*. 2020;16:672–680.
https://doi.org/10.1016/j.jalz.2019.08.193