Classification of Health Literacy and Cognitive Impairments Using Higher-Order Kinematic Parameters of the Sit-to-Stand Movement From a Monostatic Doppler Radar

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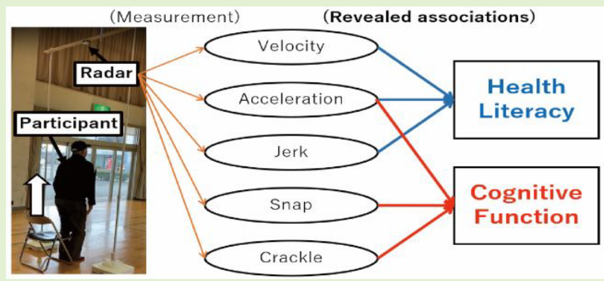
***Abstract*—To develop daily monitoring systems that can identify elderly people with cognitive functioning and health literacy impairments, this study examined elderly participants during the sit-to-stand (STS) movement by using a Doppler radar to gather kinematic information for assessing any associations between those data and factors related to both cognitive functioning and health literacy. More specifically, we used Doppler radar systems to measure kinematic parameters related to the STS movement among 170 community-dwelling elderly participants aged 65 years and older, who were classified into good or bad health literacy groups and cognitive-healthy or cognitive- impairment groups based on the results of conventional paper-based tests designed to assess health literacy and cognitive functioning, respectively. The Doppler radar measured kinematic parameters for not only velocity, acceleration, and jerk (the time derivative of acceleration), but also higher-order derivative parameters: snap (the time derivative of jerk) and crackle (the time derivative of snap). Intergroup differences between the measured kinematic parameters were then compared using Welch's t-test. The results revealed that health literacy impairments were associated with velocity, acceleration, and jerk, while cognitive impairments were associated with the higher-order derivative parameters, snap and crackle. These findings show that the Doppler radar is an effective tool to distinguish impairments between health literacy and cognitive functioning based on the extraction of higher-order derivative parameters during the STS movement. The results should lead to the development of unconstrained monitoring systems that can detect early signs of impairments in both cognitive functioning and health literacy among the elderly.**



***Index Terms*— Doppler radar, motion analysis, statistical analysis.**

I. Introduction

FELDERLY patients, daily health status assessments are promising ways to detect and prevent diseases that are closely related to both healthy life expectancy and caregiver burdens. For example, many studies have reported that low health literacy and cognitive impairment are factors that can predict mortality [1]–[3]. In this regard, health literacy is one of the most efficient factors used to predict physical and mental health. In fact, it can even be used to predict the risk of developing specific health problems, including asthma and bowel disease [4]–[6]. Further, cognitive functions are strongly related to dementia and pre-dementia (mild cognitive impairment), which can thus be detected through simple and unconstrained techniques designed to assess health literacy and cognitive functioning. While paper-based tests and/or interviews are typically used to asses both health literacy [7], [8] and cognitive functioning [9], [10], these approaches are difficult to implement on a daily basis because they require questioners and graders. It is also inappropriate to frequently and iteratively use such tests due to the fixed nature of their questionnaires.

To address this kind of issue, remote sensing techniques have become a major area of research toward the development of daily health monitoring systems. For instance, Li *et al.* [11] reported on a multisensory approach that was used to achieve accurate classifications for daily activities and fall motions

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(i.e., via accelerometer, gyroscope, magnetometer, and radar), while in-home sensing techniques involving wireless pressure, contact, and infrared technology have been used to assess activities of daily living (ADL) [12]–[14]. Further, some researchers have detected cognitive impairments via in-home monitoring approaches designed to sense gait deterioration and other issues related to physical functioning [15]. However, most of these techniques require the installation of many environmental sensors, with accelerometric and gyroscopic approaches even requiring the subjects themselves to wear sensors that may be cumbersome during daily use. Cameras and depth sensors have also been employed to develop remote sensing systems for applications such as fall detection [16] and gait analysis [17]. However, the accuracy of these systems is highly dependent on light conditions. In addition, their velocity measurement accuracy is insufficient because these sensors measure position information and do not measure velocity information directly.

To solve these problems, we recently developed a Doppler radar-based unconstrained sensing technique designed to monitor basic ADLs such as walking, standing up, and sitting down, thereby remotely assessing a variety of cognitive and physical functions related to ADL performance [18], [19]. More specifically, the Doppler radar can remotely measure the velocities of various body parts by taking short-term measurements, such as a few gait cycles during walking and one-time sit-to-stand (STS) movements. Importantly, the technology can be used to take these measurements in low-light conditions and environments containing many static obstacles. Based on these merits, many high-accuracy Doppler radar techniques have been developed for human motion recognition [20], [21] and fall detection [22]. Thus, a Doppler radar-based motion measurement system has great potential for application in the daily unconstrained monitoring of elderly patients. As examples of radar systems for such applications, the detection of concussion impairment via radar gait measurement [23] has been reported, and there have been recent investigations into applications related to simple clinical motion analysis [24]. One of the most notable merits of the Doppler radar is that it can easily measure detailed kinematic information, such as acceleration during the STS movement and leg velocity while in gait; that is, the technology can be used to measure functions of greater complexity when compared to the simpler motion parameters assessed in more conventional studies, such as mere gait speed and the time needed to complete STS movements. By using extracted kinematic parameters, our previous studies have successfully identified elderly adults with reduced ADL performance [18] and cognitive function impairments [19] based on the deterioration of physical functions while walking or during the STS movement.

Although various types of motion can be used to assess cognitive functioning and health literacy (e.g., gait and other complex ADLs), this study focused on the STS movement, which was chosen because the measurement process does not require large observation areas or long-term monitoring. Although there are well-known associations between several cognitive functions and gait [19], [24], [25], only weak correlations have been observed between the time needed to complete the five-times sit-to-stand (5STS) test and those functions [26]–[28]. Thus, no previous studies have demonstrated associations between cognitive functioning and the STS movement using detailed kinematic information. Based on the abovementioned weak correlations, however, we hypothesized that the more detailed kinematic parameters taken via a Doppler radar could be used to establish clear associations between cognitive functions and the STS movement. If such associations exist, an efficient monitoring system can be developed because the measurement of the STS movement does not require a large observation area, in contrast to gait measurements. Furthermore, various application scenes that can measure the STS movement in daily activities are considered (e.g., the STS movement in a restroom). Additionally, as a promising academic contribution, the discovery of the effectiveness of STS will aid research in the fields of epidemiology, physiotherapy, and biomechanics with respect to investigations on the relationship between health status and basic ADL (e.g., the combination of STS information and the generally used gait information will lead to new findings).

Although extensive epidemiological studies have found significant relationships between lower health literacy and impairments to physical functioning [4], [29]–[32], none appear to have reported on this issue based on the use of motion sensing information. Thus, remote sensing phenomena for health literacy via basic ADL are unknown. Following their other findings, however, we also hypothesized the existence of significant associations between the deterioration of kinematic parameters related to the STS movement and lower health literacy. Further, given that the effects of impairments to health literacy and cognitive functioning could be separately extracted from the measurement results, such information would be useful for concretely understanding the health status to establish care programs and/or rehabilitation plans based on individual needs.

This study extracted kinematic parameters related to the STS movement by using a Doppler radar to investigate their associations with health literacy and cognitive functioning among elderly participants aged 65 years and older. The main aim was to clarify which (if any) detailed STS parameters were significant indicators of related impairments. In our previous study using a Doppler radar [18], we measured several factors related to STS movements, including time, velocity, acceleration, and jerk (the time derivative of acceleration). In this study, we thus extracted and considered measurements for those same factors, in addition to high-order derivative parameters known as snap (the time derivative of jerk) [33], [34] and crackle (the time derivative of snap) [33], [35]. This was done to pursue more significant kinematic information for assessing health literacy and/or cognitive function. The contributions of this study are as follows.

- Novel Doppler radar application for the detection of impairment in health literacy was presented for the first time. Furthermore, this paper is also the first report on the remote sensing capability of health literacy.
- The higher-order kinematic parameters of snap and crackle in STS movement were revealed as new sensor phenomena for detecting cognitive impairment.

The estimation process for these parameters from the Doppler radar spectrogram was also presented.

- Experimental results revealed that health literacy and cognitive functioning were significantly associated with different kinematic parameters; cognitive impairment was mainly associated with higher-order derivative parameters, which were not positively used in conventional studies.
- We established that STS measurements taken via a Doppler radar could be used to distinguish their effects on physical functioning with regard to impairments in health literacy and cognitive functioning. These findings can establish the effectiveness of kinematic information on STS movement (not only the well-used gait information) in health status assessment, which was not clearly demonstrated in previous conventional studies.

II. Methods and Procedures

A. Participants and Experimental Procedures

Participants included a total of 170 elderly aged 65 years and above (67 men and 103 women; mean age of 74.0 ± 5.34 years; mean height of 156.9 ± 8.83 cm; mean weight of 55.2 ± 9.22 kg). None of the participants had Parkinson's disease, sarcopenia, or arthritis. All participants were able to perform the standing-up movement from a chair without assistance from others and could walk without walking aids. All measurements were taken in a community setting.

Participants were first administered paper-based tests to evaluate their health literacy and cognitive functioning. Specifically, health literacy was evaluated using the Newest Vital Sign (NVS) tool [8], while cognitive functioning was evaluated using a digit symbol substitution test (DSST) [10]. These tests are further explained in Section II-B. Participants subsequently took an STS test while being monitored via a Doppler radar, in which case we extracted relevant kinematic parameters (including high-order derivative parameters) from the radar received signals. This is described in more detail in Section II-C. Finally, statistical analyses were conducted to clarify any associations between the extracted kinematic parameters and both the NVS and DSST results. This is further explained in Section II-D.

This study's experimental protocol was approved by the ethics committee at Toyama Prefectural University (approval no. H29-1). Participants were first given written and verbal instructions explaining the testing procedures. Written consent was then obtained from each participant prior to testing.

B. Health Literacy and Cognitive Functioning Tests

We used the NVS to classify participants into good and bad literacy groups, while the DSST was used to classify them into cognitive-healthy and cognitive-impairment groups. This study evaluated statistical differences between kinematic parameters taken during the STS movement for both group types.

The NVS is a simple paper-based test designed to objectively evaluate health literacy [29], [8]. It specifically evaluates skills for reading, understanding, and acting upon health information via an interpretation test of a specially designed

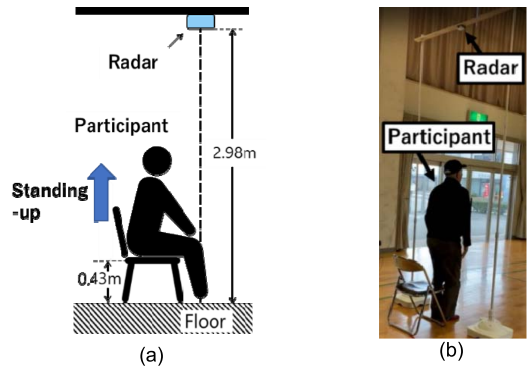

Fig. 1. Doppler radar sensing system for measuring STS movements: (a) the measurement setup and (b) experimental site.

ice-cream nutrition label (details are available in [8]). The maximum score is 6 points, with scores ≤ 1 point suggesting a high likelihood of limited health literacy [8]. Thus, this study classified participants with NVS scores ≤ 1 into the bad literacy group, while those with NVS scores > 1 were placed into the good literacy group.

The DSST is a paper-based test designed to evaluate cognitive functioning in the domain of information processing speed; it is a subtest of the WAIS-III [3]. The DSST indicates a digit–symbol pair, for which participants are required to write down the corresponding symbol under each digit as quickly as possible. DSST scores are equal to the number of correctly written symbols within a two-minute period. The DSST test sheet is available in [3]. DSST scores less than 49 indicate possible cognitive impairment [36]. This study therefore classified participants with DSST scores ≤ 48 into the cognitive-impairment group, while those with DSST scores > 48 were placed into the cognitive-healthy group.

C. Doppler Radar Measurements of STS Movements, Including High-Order Derivative Parameters

The kinematic parameters of the STS movement were extracted using Doppler radar measurements. The Doppler radar system used in this study was similar to those used in our previous study [18]. Fig. 1 shows the measurement setup and experimental site. As shown, the radar was placed just above participants when they were standing. It was set at a height of 2.98 m, while the height of the seat below was 0.43 m. Participants first sat down on the chair with a self-selected foot position and were then instructed to stand up at a comfortable speed. No restrictions on clothing or shoes were imposed.

The Doppler radar transmitted a 24-GHz continuous sinusoidal wave with an effective isotropic radiated power of 40 mW to each participant. The directivity of the radar was ±14°. Fig. 2 shows a block diagram of the Doppler radar system. Received reflected waves were demodulated using the transmitting signal; we obtained the demodulated in-phase/quadrature signals as received signals after filtering, amplification, and analog-to-digital conversion with a sampling frequency of 600 Hz corresponding to a measurement velocity range of ± 1.875 m/s.

Received signals were composed of Doppler frequencies corresponding to the velocities of the scattering centers on each body part (e.g., head, torso, and arms); these were

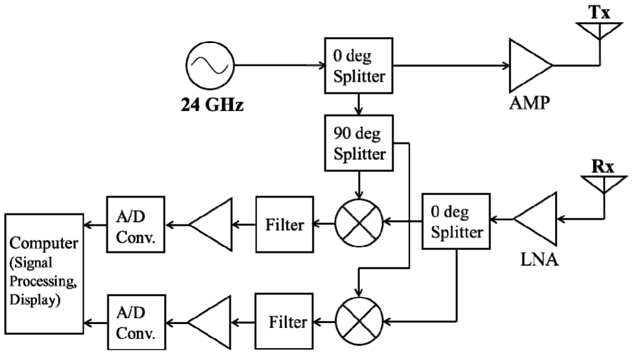

Fig. 2. Block diagram of the radar system.

expressed as a spectrogram using a short-time Fourier transform (STFT) method. The received signal was defined as $s(t)$; its STFT of $S(t,\ f_{\mathrm{d}})$ was then calculated, where t is time and f_{d} is the Doppler frequency. The Hamming window function with a length of 128 samples was empirically used for the STFT process. Velocity v_{d} was calculated with $v_{\mathrm{d}} = \lambda_0 f_{\mathrm{d}}/2$, where λ_0 is the wavelength of the 24.0-GHz sinusoidal wave (1.25 cm). Using this relationship to f_{d} of $S(t,\ f_{\mathrm{d}})$, we obtained the spectrogram, which expresses the time–velocity distribution of the received signal $|S(t,\ v_{\mathrm{d}})|^2$. Additionally, we removed the components of $v_{\mathrm{d}} = 0$ from the received signals using a one-dimensional Butterworth high pass filter, with a cutoff frequency of 30 Hz, before the calculation of the spectrogram to eliminate echoes from static targets such as the chair. Note that this filtering process did not affect the extraction results of the STS kinematic parameters. Fig. 3(a) shows an example of the spectrogram for the STS movement. We could confirm characteristic components indicating the temporal variation of v_{d} with relatively strong received powers corresponding to the standing-up motion (positive velocity components) and bending motions of the back before standing up (negative velocity components). We can confirm from Fig. 3(a) that other echoes corresponding to multipath effects (such as the effects of reflection from the chair) and other micromotions (such as body oscillation) are sufficiently small to extract the characteristic components corresponding to the motions of the head and body.

We extracted kinematic parameters, including high-order derivative parameters of the STS movement, using the extracted spectrogram shown in Fig. 3(a). The extracted parameters were velocity, acceleration, jerk (the time derivative of acceleration), snap (the time derivative of jerk and fourth derivative of position) [34], and crackle (the time derivative of snap and fifth derivative of position) [35]. We first extracted the median velocity components $v_{\mathrm{dm}}(t)$ to extract the characteristic components in the spectrogram [18]. Fig. 3(b) shows the extracted $v_{\mathrm{dm}}(t)$ from the spectrogram shown in Fig. 3(a); we could confirm that the time series of the main components was extracted. We calculated the mean, maximum, and minimum values for $v_{\mathrm{dm}}(t)$, as the kinematic parameters of the STS movement, as $v_{\mathrm{mean}} = \mathrm{E}[|v_{\mathrm{dm}}(t)|]$ (E[ ] indicate the mean with respect to t), $v_{\mathrm{max}} = \mathrm{Max}\ v_{\mathrm{dm}}(t)$, and $v_{\mathrm{min}} = \mathrm{Min}\ v_{\mathrm{dm}}(t)$, respectively. Additionally, the time to perform the standing-up motion T_{sta} was calculated with the process described in [18]. Then, the time derivatives of $v_{\mathrm{dm}}(t)$ were calculated to estimate higher-order derivative parameters. In this study, we calculated not only the acceleration and jerk, which are commonly used, but also the higher-order derivative parameters snap and crackle. With $v_{\mathrm{dm}}(t)$, we calculated $a_{\mathrm{dm}}(t) = \mathrm{d}v_{\mathrm{dm}}(t)/\mathrm{d}t$, jerk $j_{\mathrm{dm}}(t) = \mathrm{d}a_{\mathrm{dm}}(t)/\mathrm{d}t$, snap $s_{\mathrm{dm}}(t) = \mathrm{d}j_{\mathrm{dm}}(t)/\mathrm{d}t$, and crackle $c_{\mathrm{dm}}(t) = \mathrm{d}s_{\mathrm{dm}}(t)/\mathrm{d}t$. Empirically designed moving-average low-pass filters with an average length of 0.15 s were used to remove small errors in each time series. Fig. 3(c), (d), (e), and (f) show the results of these signals. Simple kinematic parameters with respect to higher-order derivatives were thus calculated similarly to the velocity parameters as follows: $a_{\mathrm{mean}} = \mathrm{E}[|a_{\mathrm{dm}}(t)|]$, $a_{\mathrm{max}} = \mathrm{Max}\ a_{\mathrm{dm}}(t)$, $a_{\mathrm{min}} = \mathrm{Min}\ a_{\mathrm{dm}}(t)$ (acceleration parameters), $j_{\mathrm{mean}} = \mathrm{E}[|j_{\mathrm{dm}}(t)|]$, $j_{\mathrm{max}} = \mathrm{Max}\ j_{\mathrm{dm}}(t)$, $j_{\mathrm{min}} = \mathrm{Min}\ j_{\mathrm{dm}}(t)$ (jerk parameters), $s_{\mathrm{mean}} = \mathrm{E}[|s_{\mathrm{dm}}(t)|]$, $s_{\mathrm{max}} = \mathrm{Max}\ s_{\mathrm{dm}}(t)$, $s_{\mathrm{min}} = \mathrm{Min}\ s_{\mathrm{dm}}(t)$ (snap parameters), $c_{\mathrm{mean}} = \mathrm{E}[|c_{\mathrm{dm}}(t)|]$, $c_{\mathrm{max}} = \mathrm{Max}\ c_{\mathrm{dm}}(t)$, $c_{\mathrm{min}} = \mathrm{Min}\ c_{\mathrm{dm}}(t)$ (crackle parameters).

D. Statistical Analysis

Based on extracted kinematic parameters, p-values were calculated using Welch's t-test to evaluate statistical differences between both the good and bad literacy groups and cognitive-healthy and cognitive-impairment groups, while the effect size was calculated using Hedge's g [37] to evaluate the magnitude of any differences. We set significance levels to $p = 0.05$. These values were calculated for all kinematic parameters extracted using the Doppler radar. Differences between NVS and DSST scores were then compared to distinguish their associations with the physical functions needed to perform the STS movement.

Further, to investigate the possibility of screening the bad literacy and cognitive-impairment groups using the extracted parameters, we performed the classifications using a support vector machine (SVM) and their evaluations using the ROC curve [38]. The kinematic parameters that indicate significant differences between the two groups were selected as the feature parameters in the SVM. The SVM used a Gaussian kernel function and the parameters of the SVM were optimized via grid search. We used hold-out validations to depict the ROC curves for the classifications of both good and bad literacy groups and cognitive-healthy and cognitive-impairment groups. For each validation, the SVM was trained using 90% of the data of participants, and the remaining 10% of the data were used as test data. Then, 100 trials for the hold-out validations were conducted by randomly varying the training data selection. The mean sensitivity and specificity across the 100 tests were calculated to depict the ROC curves. The screening capabilities were evaluated using the area under the ROC curve (AUC) and compared with random guesses of AUC = 0.5.

III. Results

Table I summarizes the results of the parameter extraction and evaluation and Welch's t-test for NVS. For the extracted parameters, the absolute values of v_{mean}, v_{max}, a_{max}, j_{max}, and j_{min} of the good literacy group were significantly larger than those of the bad literacy group with $|g| > 0.3$, which indicates

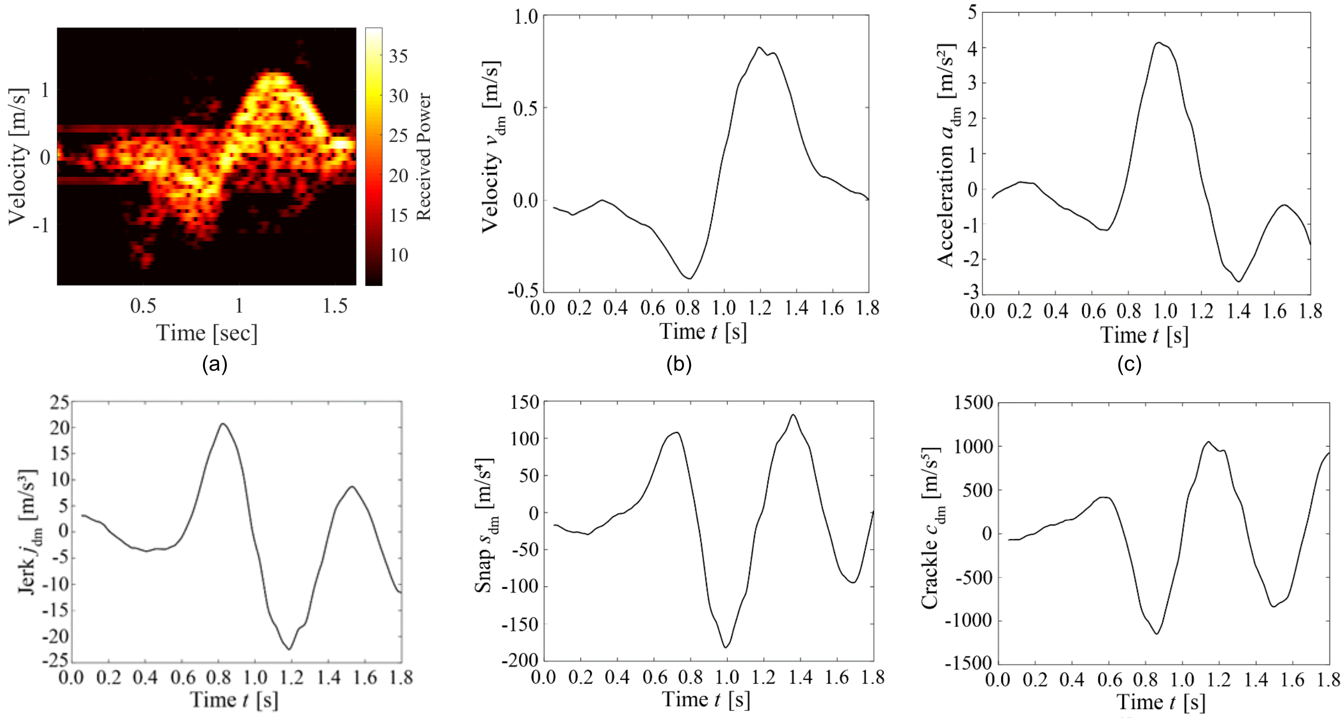

Fig. 3. Example of the processing of the received signals: (a) a spectrogram for STS movement, (b) median frequency components $v_{dm}(t)$, (c) the time series of acceleration $a_{dm}(t)$, (d) the time series of jerk $j_{dm}(t)$, (e) the time series of snap $s_{dm}(t)$, and (f) the time series of crackle $c_{dm}(t)$.

that the overlap of the distributions of each parameter of the two groups is approximately smaller than 80%. However, no significant differences were found in regard to the other parameters,

including snap and crackle. Fig. 4 shows examples of plots for the kinematic parameters velocity, acceleration, snap, and crackle for all participants. As indicated in Fig. 4(a) and (b), although we found no clear boundary for correctly classifying the two groups, there was some intergroup divergence. We also confirmed that there were no intergroup differences regarding the higher-order derivative parameters of snap and crackle, as indicated in Fig. 4(c) and (d). Thus, only the lower-order derivative parameters of the STS movement were associated with impairments to health literacy.

Table II summarizes the DSST results. The absolute values of T_{sta}, a_{mean}, s_{mean}, s_{max}, c_{mean}, and c_{min} of the cognitive-healthy group were significantly larger than those of the cognitive-impairment group, with $|g| \geq 0.4$. However, no significant differences were found in the lower-order derivative parameters, except for a_{mean}. Fig. 5 shows examples of the plots. More specifically, Fig. 5(a) and (b) indicate no significant intergroup differences in velocity, with only slight differences in acceleration. By contrast, Fig. 5(c) and (d) show significantly larger intergroup differences in snap and crackle. We thus found that the higher-order derivative parameters of snap and crackle could be used to detect cognitive impairments among participants. This study's overall findings are summarized in Table III.

Fig. 6 presents the ROC curves for the SVM classifications of the good and bad literacy groups and the cognitive-healthy and cognitive impairment groups using the parameters that indicated $p < 0.05$; their AUCs were 0.658 and 0.667, respectively. Although these AUCs were not high in terms of the classification accuracy, significantly better results compared with the random guess (AUC = 0.5) were obtained.

IV. Discussion

A. Contributions

This study investigated STS kinematic parameters measured via a Doppler radar to test for associations between those data and impairments to both health literacy and cognitive functioning among elderly participants. In relation to the STS movement, we thus determined that health literacy impairments were associated with lower-order derivative parameters (i.e., velocity, acceleration, and jerk), while cognitive impairments were associated with higher-order derivative parameters (i.e., snap and crackle). These findings are clearly summarized in Table III. Furthermore, the screening capabilities, evaluated using the ROC curves shown in Fig. 6, demonstrated the significantly efficient accuracies of the SVM-based screening using the extracted parameters compared with the random guesses. Thus, the extracted kinematic parameters could possibly be applied to the screening of the bad literacy and cognitive-impairment groups.

Notably, this paper constitutes the first report on the remote detection of impairments to physical functioning due to lower health literacy and this is a novel finding with respect to not only Doppler radar sensing but also sensing phenomena for the remote evaluation of health literacy. Further, this study produced the first results showing clear practical uses for the higher-order derivative parameters of snap and crackle when measured during the STS movement. The mechanisms of and

TABLE I
DIFFERENCES BETWEEN GOOD AND BAD LITERACY GROUPS

	Good literacy (NVS > 1)	Bad literacy (NVS ≤ 1)	p (*: <0.05)	|g| (*: >0.3)
Number	125 (56 men)	45 (11 men)		
Age [years]	73.0 ± 4.81	76.7 ± 5.85		
Height [cm]	158.8 ± 8.32	152.0 ± 8.32		
Mass [kg]	55.6 ± 9.05	54.5 ± 9.73		
T_{sta} [s]	0.724 ± 0.184	0.720 ± 0.153	0.863	0.03
v_{mean} [m/s]	0.422 ± 0.089	0.384 ± 0.081	0.00906*	0.44*
v_{max} [m/s]	0.765 ± 0.155	0.691 ± 0.147	0.00532*	0.48*
v_{min} [m/s]	-0.305 ± 0.114	-0.282 ± 0.0957	0.196	0.21
a_{mean} [m/s^2]	2.13 ± 0.667	1.92 ± 0.631	0.0630	0.32
a_{max} [m/s^2]	4.30 ± 0.999	3.88 ± 0.930	0.0121*	0.43*
a_{min} [m/s^2]	-2.72 ± 0.851	-2.53 ± 0.894	0.202	0.23
j_{mean} [m/s^3]	12.8 ± 4.91	11.6 ± 4.94	0.174	0.24
j_{max} [m/s^3]	11.7 ± 4.80	9.71 ± 4.83	0.0218*	0.41*
j_{min} [m/s^3]	-28.9 ± 9.95	-25.6 ± 9.66	0.0491*	0.34*
s_{mean} [m/s^4]	97.0 ± 42.1	109 ± 56.2	0.182	0.27
s_{max} [m/s^4]	151 ± 62.5	166 ± 85.9	0.263	0.23
s_{min} [m/s^4]	-242 ± 79.8	-252 ± 88.7	0.530	0.11
c_{mean} [m/s^5]	1000 ± 408	1147 ± 630	0.152	0.31*
c_{max} [m/s^5]	2601 ± 930	2864 ± 1188	0.182	0.26
c_{min} [m/s^5]	-2152 ± 933	-2125 ± 976	0.876	0.03

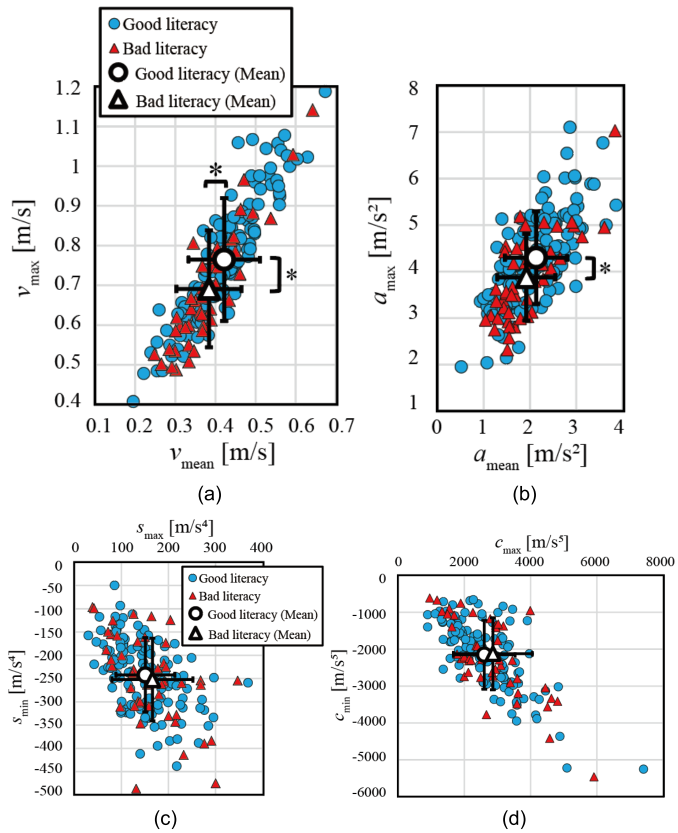

Fig. 4. Extracted kinematic parameters for good and bad literacy groups: (a) velocity (v_{mean}, v_{max}), (b) acceleration (a_{mean}, a_{max}), (c) snap (s_{max}, s_{min}), and (d) crackle (c_{max}, c_{min}). $*$ denotes the significant difference between the two groups with $p < 0.05$.

reasons behind this are more thoroughly discussed in the next subsection.

As for technical contributions, we also verified that unconstrained Doppler radar measurements taken during natural one-time STS movements could predict impairments to both health literacy and cognitive functioning. This is in contrast to the conventional 5STS test, which is generally used in epidemiological studies dealing with health status among the elderly (including health literacy and cognitive functioning) and measures physical functioning while participants quickly stand up and sit down five successive times. However, this procedure is both cumbersome and burdensome to many participants. The Doppler radar technique used in this study can measure rich kinematic information, including detailed higher-order derivative parameters during the natural STS test, using a single radar system. This makes it more effective for daily use. Further, our findings about the ability to distinguish between the effects of health literacy and cognitive function are important for the development of monitoring systems that can separately assess their effects on various health statuses based on each movement component.

In terms of the scientific contribution, we have demonstrated the effectiveness of STS movement, not only the gait information that is generally used in the evaluation of cognitive functions in various research fields, including epidemiology, physiotherapy, and biomechanics. Conventionally, many researchers have investigated the relationship between gait information and various health status information. However, this study suggests that STS movement is also effective and detailed experiments, similar to gait examinations, will lead to novel findings on the cognitive function-related kinematic and epidemiological studies. Although the degree of relations between cognitive function and the STS parameters were weak compared with the gait parameters revealed in our previous study [19], the possibility of using the STS parameters to evaluate cognitive functions and other related health status was implied in this study, and this will be effective in the discovery of unknown factors related to cognitive impairment and/or the development of novel measurement schemes, e.g., more accurate evaluation of cognitive functioning by combining gait and STS parameters, and the finding of new relationships between STS information and other domains of cognitive functions that have not been dealt with in our study, such as memory functions.

B. Reasons for Our Results

This section discusses the reasons for the significant associations found between the extracted kinematic parameters and impairments to both health literacy and cognitive function. First, we discuss how health literacy is associated with velocity, acceleration, and jerk during the STS movement. These parameters are closely related to physical functioning

TABLE II
DIFFERENCES BETWEEN THE HEALTHY AND IMPAIRED COGNITIVE GROUPS

	Cognitive-healthy (DSST > 48)	Cognitive-impairment (DSST ≤ 48)	p (*: <0.05)	$\|g\|$ (*: >0.3)
Number	136 (53 men)	34 (14 men)		
Age [years]	78.6 ± 5.24	72.8 ± 4.71		
Height [cm]	153.0 ± 7.97	157.8 ± 8.80		
Mass [kg]	55.0 ± 7.71	55.3 ± 9.58		
T_{sta} [s]	0.706 ± 0.162	0.793 ± 0.212	0.0304*	0.50*
v_{mean} [m/s]	0.417 ± 0.089	0.391 ± 0.082	0.103	0.31
v_{max} [m/s]	0.750 ± 0.157	0.728 ± 0.151	0.466	0.14
v_{min} [m/s]	-0.298 ± 0.113	-0.303 ± 0.101	0.783	0.05
a_{mean} [m/s^2]	2.12 ± 0.666	1.88 ± 0.622	0.0427*	0.36*
a_{max} [m/s^2]	4.23 ± 0.990	4.05 ± 1.02	0.383	0.17
a_{min} [m/s^2]	-2.72 ± 0.877	-2.46 ± 0.784	0.0888	0.31*
j_{mean} [m/s^3]	12.8 ±4.88	11.3 ± 4.57	0.0968	0.29
j_{max} [m/s^3]	11.3 ± 4.75	10.5 ± 5.34	0.448	0.16
j_{min} [m/s^3]	-28.5 ± 10.2	-26.1 ± 8.91	0.168	0.25
s_{mean} [m/s^4]	104 ± 47.3	85.6 ± 39.6	0.0254*	0.39*
s_{max} [m/s^4]	161 ± 71.9	131 ± 54.1	0.0100*	0.43*
s_{min} [m/s^4]	-248 ± 80.5	-234 ± 88.6	0.382	0.18
c_{mean} [m/s^5]	1079 ± 499	878 ± 354	0.00855*	0.42*
c_{max} [m/s^5]	2711 ± 1030	2509 ± 909	0.266	0.21
c_{min} [m/s^5]	-2241 ± 973	-1763 ± 693	0.00158*	0.51*

during ADLs; thus, there are important differences in STS parameters between the good and bad health literacy groups. Previous studies have also demonstrated significant relationships between lower health literacy and lower physical functioning [4], [29]–[32]. For example, Smith *et al.* [29] found a significant relationship between certain physical functions needed to perform ADLs (e.g., changing clothes) and NVS scores, while Osbom *et al.* [30] showed a significant relationship between recreational and transportation-related physical activities and health literacy, thereby providing a discussion on the related mechanism. Further, our previous study revealed that kinematic parameters related to STS were associated with the physical functions needed to perform instrumental ADLs and discussed biomechanical factors related to velocity, acceleration, and jerk [18]. Thus, current results can be explained via the linkage between the STS–physical function relationship (i.e., when performing ADLs) and the physical function–health literacy relationship.

Next, we discuss the associations between the higher-order derivative parameters of snap/crackle and cognitive impairment. Although it is difficult to grasp the detailed mechanisms based on our results, two conventional results

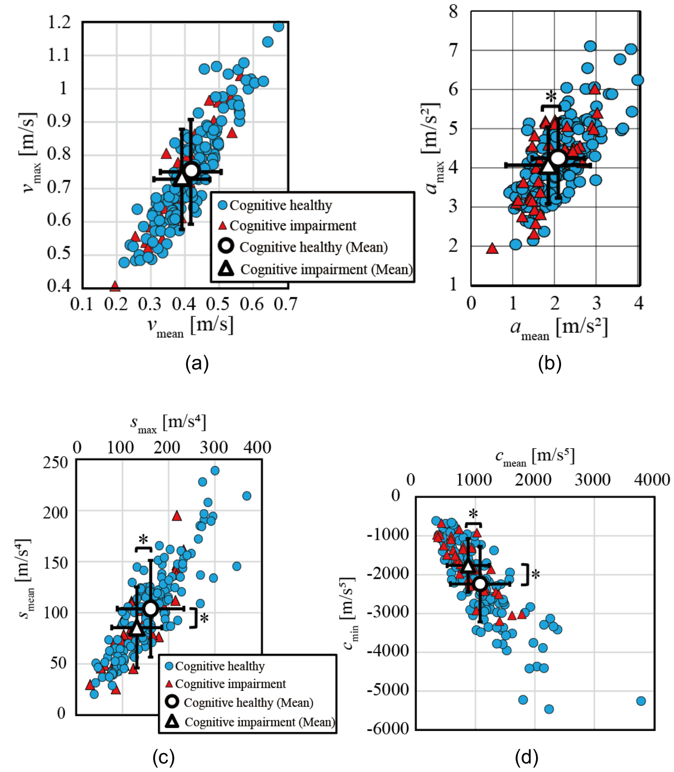

Fig. 5. Extracted kinematic parameters for cognitive-healthy and cognitive-impairment groups, including (a) velocity (v_{mean}, v_{max}) (b) acceleration (a_{mean}, a_{max}), (c) snap (s_{max}, s_{mean}), and (d) crackle (c_{mean}, c_{min}). * denotes the significant difference between the two groups with $p < 0.05$.

TABLE III
SUMMARY OF THIS STUDY'S NOVEL FINDINGS

[Dimension]	STS Parameter	Health literacy	Cognitive function
[s]	Time	not significant	**significant**
[m/s]	Velocity	**significant**	not significant
[m/s^2]	Acceleration	**significant**	**significant**
[m/s^3]	Jerk	**significant**	not significant
[m/s^4]	Snap	not significant	**significant**
[m/s^5]	Crackle	not significant	**significant**

provide evidence; that is, weak correlations between cognitive functions and the time to complete the 5STS test and the effectiveness of using detailed kinematic information via derivative operations when considering the mechanisms behind the motions used during gait and STS. There are many reports on the significant associations between cognitive functions and both time [26]–[28] and velocity [28] during the 5STS test. However, the degrees of those associations are weak. This study obtained consistent results supporting those conventional studies; that is, regarding the weak associations between cognitive functioning and STS time T_{sta} and the slightly larger effect size g of the STS velocity v_{mean} without any significant difference indicated by $p > 0.05$ ($p = 0.0677$). However, our results also revealed significant associations with snap and crackle, even though velocity, acceleration, and jerk did not show significant associations. Indeed, some researchers

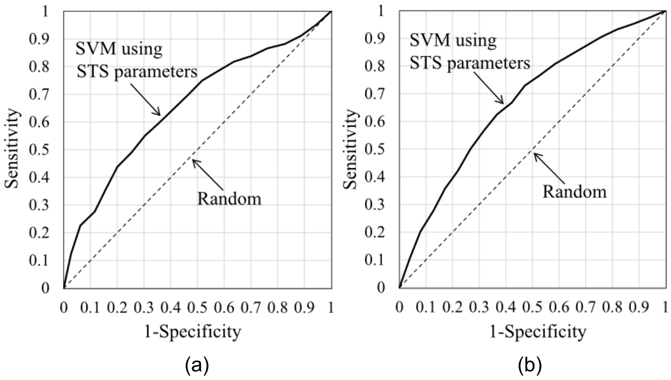

Fig. 6. ROC curve analysis results using SVM: (a) classification of the good and bad literacy groups. (b) classification of the cognitive-healthy and cognitive-impairment groups.

have already reported that higher-order derivative parameters such as acceleration and jerk are more important factors for the stability and smoothness of STS movements than velocity [39], [40]. Similarly, other studies have investigated the effectiveness of snap and crackle for expressing the smoothness of human motion [34], [35]. As such, the literature shows that detailed kinematic information corresponding to the slight deterioration of motion smoothness during the STS movement may indicate cognitive impairment. This can be detected via higher-order derivative operations, which explains our results.

C. Limitations of This Study

This study had three main limitations. The first and most important is that we took measurements from a relatively small number of participants. As such, state-of-the-art statistical analysis methodologies such as deep learning were inefficient. Specifically, only one iteration of STS data was taken for each of the 178 participants. This sample size was too small for machine-learning approaches that could have otherwise extracted more detailed parameters in order to better classify participants into groups. As indicated in the SVM results presented in Fig. 6, although the impairments in health literacy and cognitive impairments were screened to some extent, more accurate classification capability might be recommend for the practical use. Thus, future studies should take measurements from larger groups to apply various advanced statistical methods and to develop more sophisticated signal processing schemes for the improvement of classification accuracy. This is important, as this study only showed significant associations between groups.

Second, the measurement process was limited. Although the Doppler radar is able to measure human motion without depending on static obstacles or clothing, the position of the radar system and height of the chair affected the measurement results. This means that additional experiments are required in which other chairs and radar systems are placed at various positions throughout the study environment, thus validating technological practicality.

Third, this study considered the factors of limited cognitive functioning and health literacy, but this also leads to important future tasks. We determined cognitive functioning based on information processing speeds via the DSST. However, there are many other domains to cognitive functioning, including memory, language, and executive functions. For example, our previous study showed that gait parameters depend on the considered cognitive domain [19]. This means that similar investigations into STS movement are also important. If such significant relationships to other various cognitive functions are revealed, new factors related to cognitive impairment and dementia might be found using STS movement (not only gait); these factors could be scientifically important for a wide research area involving not only sensor technology but also epidemiology and biomechanics (and sensor systems for applications in such research areas). Further, while the NVS can be used to screen people with lower health literacy, other investigative tools are available for evaluating its various aspects [1]–[8]. Thus, future research should clarify the associations between kinematic parameters extracted via the Doppler radar and other various health literacy scales. This would produce more detailed information on health literacy in general.

V. Conclusion

This study used Doppler radar technology to measure kinematic parameters during the STS movement, thus showing associations with those data and impairments to both health literacy and cognitive functioning among elderly participants aged 65 years and older. Consequently, we revealed significant differences between good and bad health literacy groups in regard to the conventionally used lower-order derivative parameters of velocity, acceleration, and jerk. We then uniquely demonstrated significant differences between cognitive-healthy and cognitive-impairment groups based on the higher-order derivative parameters of snap and crackle. Through these results, we discovered new sensor phenomena that the kinematic information sensed using the Doppler radar includes the deterioration of physical functions related to their impairment. In addition, the Doppler radar was used to discover that different parameters were associated with impairments to health literacy and cognitive functioning. These findings can be used to develop systems that are able to identify impairments to both conditions via unconstrained daily monitoring as novel applications for the Doppler radar.

Future experiments are needed to resolve the limitations described in the previous section. In addition, the use of multiple Doppler radars and other various types of motion sensors (e.g., depth sensors and cameras) can improve overall detection accuracy. It is also promising to construct practical daily monitoring systems based on sensor fusion while considering issues of both cost and privacy. Combined with our previous results on STS and gait [19], this study's results should also aid in developing methodologies designed to monitor various other ADLs, such as the stand-to-sit, getting-up, and turn-to-sit movements.

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