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Using Micro-Doppler Radar to Measure Gait Features Associated With Cognitive Functions in Elderly Adults

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ABSTRACT This paper used micro-Doppler radar (MDR) measurements to investigate the significance of associations between cognitive functions and gait features of elderly persons. The aim of this paper was to develop a system that would enable the risks of developing dementia and related diseases to be monitored remotely on a daily basis. Study participants were adults aged 75 years and older. Gait velocity parameters corresponding to the walking speed and leg and foot velocities were remotely extracted via a simple 24-GHz MDR system in real time. The relationships between the extracted gait velocity parameters and the global cognition and cognitive functions in various cognitive domains (processing speed, memory, executive function, and language domains) that were assessed by conventional paper- and question-based tests were statistically analyzed. Our results revealed that, apart from the walking speed, which was mainly considered in a previous study, other parameters reflecting the leg and foot velocities are effective for the detection and classification of elderly participants with lower cognitive functions in the various cognitive domains. In particular, the statistical significance of the association of the leg velocity in the swing phase with the results of all the cognitive function tests is larger than that of the walking speed. Another important finding is that different gait velocity parameters are associated with each cognitive domain and this means that the MDR-based gait measurement can be used to determine which cognitive domain has deteriorated.

INDEX TERMS Biomedical informatics, Doppler radar, gait recognition, statistical analysis.

I. INTRODUCTION

Dementia is a progressive global cognitive impairment syndrome. Thus, early detection and prevention of dementia based on the daily assessment of cognitive functions is important for elderly adults. Many types of tests to assess the cognitive functions have been developed and are widely used, such as the Mini-mental state examination (MMSE) [1], [2]. This test is known as a screening test for dementia and for assessment of the global cognitive function, which is composed of various cognitive domains such as those pertaining to memory and language. Various tests to assess the cognitive function in each cognitive domain are also widely used [3]–[6]. However, these tests are paper- and/or question-based tests that require a questioner/grader, which complicates daily monitoring.

The relationships between reduced walking ability and cognitive impairment and dementia have been investigated in numerous studies [6]–[17]. These studies indicate that a gait measurement technique would be promising to monitor cognitive functions on a daily basis. However, walking speed is generally measured using a simple walking test timed with a stopwatch, known as the 10 m (or another distance of the order of 1 m) walk test [7]–[13]. This test is cumbersome because it involves a constrained environment for subjects and requires support by physiotherapists. Although sensor-based techniques such as a pressure mat [14]–[17] and accelerometry [18] have been used, these techniques also constrain the participants. In addition, the installation

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of the sensor equipment is cumbersome compared with the remote sensors introduced in this study. In this regard, optical techniques (laser range finder, depth sensor, and camera) are simple and allow automatic and unconstrained gait measurements [19], [20]. However, daily monitoring using camera-based methods could be a privacy invasion. In addition, these methods perform poorly in low-light conditions and their performance could be adversely affected by the subject's clothes. In terms of the laser range finder technique, its measurement area is narrow and the acquisition of the motion of the whole body is difficult. Although the scanning of the laser beam can solve this problem, the lasers with multiple scanning lines are expensive compared with other sensors and are physically large compared with radar-based monitoring systems that are presented in this paper. Furthermore, the abovementioned techniques only measure representative parameters (e.g., gait speed, cadence, and swing/stance times) and more accurate acquisition of detailed gait parameters such as leg and foot velocities is difficult. Most conventional studies on the evaluation of cognitive functions have investigated their relationship to walking speed only (and a relatively small number of studies focused on walking rhythm such as cadence and the time required for leg swinging) [6]. Thus, details of the relationship between gait information and cognitive function are not available.

Micro-Doppler radar (MDR) is a promising candidate that avoids the problems associated with the techniques described above [21]–[30]. MDR can remotely measure the velocities of moving objects based on the Doppler effect without constrained environment for subjects and can operate in low-light conditions [21], [22]. This method does not involve privacy concerns, because only velocity information is obtained. Moreover, the physical size of MDR devices is appropriately small for daily monitoring in homes, hospitals, and other such places [22]–[24]. Furthermore, the MDR can measure wide area without scanning of antennas or beams. MDR enables the velocity of each body part to be measured as the gait features of individuals [25], [26]. The effectiveness of MDR has been verified for human motion classification [25], [27], [28], multiple pedestrian recognition [29], [30], and rehabilitation application [22]. In our previous work [23], the gait classification of young and elderly adults was achieved using not only their walking speed but also their leg velocity parameters that can be easily extracted with MDR. Furthermore, we showed that these gait velocity parameters can improve the screening accuracy of memory impairment [24]. Thus, we can predict that these parameters are effective for the assessment of various cognitive functions and the screening of dementia, without the need of professionals.

In this study, we investigate the gait feature parameters extracted from the MDR and their association with the cognitive functions of elderly adults aged 75 years and above. The main aim is to clarify the gait parameters that significantly indicate the deterioration of global cognition and the cognitive function in each cognitive domain; the cognitive domains we considered are processing speed [3], memory [4], executive function [5], [31], and language [6], [32]. Four types of cognitive function tests are used to assess the global cognition and cognitive functions in the above cognitive domains. We also conduct the walk test using the MDR and extract the gait velocity parameters. The relationships between the scores of the cognitive function tests and extracted parameters are statistically analyzed and the parameters associated to each cognitive domain are clarified. The analysis assessed the correlation between the cognitive function and the MDR-measured gait parameters and the differences in high- and low-score groups of cognitive function tests and their classification capability using the extracted parameters. Based on the results, we discuss the applicability of the MDR to evaluate the cognitive functions and the reasons for the associations between extracted parameters and each cognitive domain.

II. METHODS

A. PARTICIPANTS AND EXPERIMENTAL PROCEDURE

The participants were 74 elderly adults aged 75 years and above (29 men and 45 women, mean age 79.0 ± 4.11 years, mean height 155.2 ± 8.61 cm, mean mass 54.4 ± 8.03 kg). All participants were able to ambulate at least 10 m without the assistance of another person or walking aids. They first performed the four cognitive function tests described in Section II-B. The participants subsequently performed a walk test using the MDR and we extracted the gait parameters from the MDR signals, as explained in Section II-C. Finally, statistical analyses were conducted to clarify the association of the gait parameters with the results of the cognitive function tests, as explained in Section II-D.

The experimental protocol was approved by the local ethics committee (Toyama Prefectural University, approval no. H29-1). Participants were provided with written and verbal instructions of the testing procedures, and written consent was obtained from each participant prior to testing.

B. COGNITIVE FUNCTION TESTS

The following four cognitive function tests were used. These evaluate the global cognition and the cognitive functions of various domains [6], [31]. An outline of the cognitive domain and corresponding tests is shown in Fig. 1. The following subsections contain an outline and the procedure of each test.

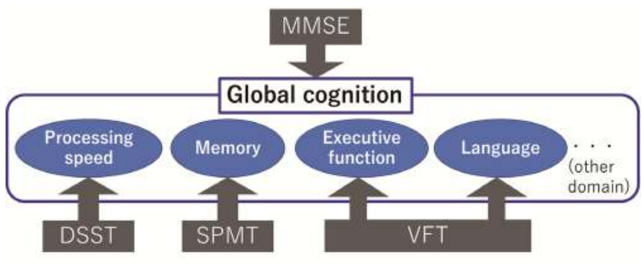

FIGURE 1. Outline of cognitive function, cognitive domain, and corresponding cognitive function tests.

1) MINI-MENTAL STATE EXAMINATION (MMSE)

The MMSE is a commonly used paper- and question-based test to detect deterioration of global cognition and to screen dementia [1]. This consists of simple questions and problems related to various cognitive domains such as:

- Identifying the current day of the week, followed by the date, month, season, and year.
- Memorizing a short list of objects and then repeating the list.
- Writing a short sentence that is grammatically correct.

All problems of the MMSE test are provided in [1]. The questioner/grader asks the participants the questions of the test and assigns a score to each section based on their answers. The maximal score is 30 points. A score between 24–30 points indicates normal cognition and a score of less than 24 points indicates cognitive impairment [1], [2].

In this study, participants with MMSE scores of >23 points were classified into high-score groups and those with mmse scores ≤ 23 points into low-score groups. The statistical difference between the two groups was investigated to explore the effective gait parameters for the assessment of the overall cognitive function.

2) DIGIT SYMBOL SUBSTITUTION TEST (DSST)

The DSST is a paper-based test to quantitatively evaluate the cognitive function in the domain of processing speed (known as information processing speed or cognitive processing speed) and is a subtest of the WAIS-III test [3]. The DSST entails indicating a digit-symbol pair, and the participants are required to write down the corresponding symbol under each digit as quickly as possible. The DSST score equals the number of symbols written correctly within 2 minutes. The test sheet of the DSST is published in [3].

Generally, the score of the DSST is used directly to investigate the relationships to the walking speed and various other variables [8]–[10]. Thus, the correlations between DSST score and MDR gait parameters were analyzed in this study.

3) SCENERY PICTURE MEMORY TEST (SPMT)

The SPMT is a paper- and question-based test intended to detect memory impairment using a picture of scenery [4]. First, participants view a line drawing of a living room containing 23 familiar objects (see [4, Fig. 1]) for 60 s and are instructed to memorize the objects. Next, the digits forward test is conducted to distract the participants. Subsequently, the participants are asked to recall the objects in the picture without imposing any limitation in terms of time. The number of objects that are correctly recalled is the score of the SPMT, which has a maximum score of 23 points. An SPMT score of less than 10 points indicates memory impairment [4].

In this study, the participants with SPMT scores of ≥ 10 points were classified into high-score groups and those with spmt scores <9 points into low-score groups. The statistical difference between the two groups was analyzed to determine the gait parameters related to the memory domain.

4) VERBAL FLUENCY TEST (VFT)

The VFT is a question-based test to investigate the cognitive functions in the executive function [31] and the language [32] domains. The VFT requires participants to produce as many words as possible from a category in a given time. The most frequently used category is animal names and the given time is usually one minute [5]. The score of the VFT is the number of words correctly answered. A VFT score of less than 11 points indicates a high-risk of dementia [5].

In this study, participants with VFT scores of ≥ 11 points were classified into the high-score group and those with VFT scores <11 points into the low-score group. The statistical difference between these two groups was analyzed to investigate the gait parameters related to the cognitive domains in language and the executive function domains.

C. GAIT MEASUREMENT WITH MICRO-DOPPLER RADAR

1) MEASUREMENT SYSTEM AND SITUATION

An MDR measurement system similar to that in [23] and [24] was used for this study. Fig. 2 shows the gait measurement situation and the MDR specifications. A single MDR was installed at a height of 0.86 m. This height is approximately equivalent to a height of a center of mass calculated by the mean height of the subjects (The height of the center of mass is generally known as 0.55–0.56 times of the body height). The MDR transmitted a continuous wave centered at a frequency of 24 GHz to a pedestrian participant. The received signals were demodulated by the transmitted signal, and are composed of the Doppler frequencies corresponding to the walking velocities of the scattering centers on the body parts. The sampling frequency of the received signal is set to 600 Hz, which corresponds to the maximum measurement velocity of 3.75 m/s.

MDR specification

Frequency	24 GHz
Waveform	Sinusoidal
Installed height	0.86 m
EIRP	40 mW
3dB beamwidth	±35° (Horizontal), ±14° (Vertical)
Physical size	6 cm (W) × 2cm(D) × 7cm (H)

FIGURE 2. Outline of MDR experiments: experimental site (left), MDR specification (right).

In the MDR walking test, the participants walked toward the radar equipment along a 10-m walkway at a self-selected comfortable pace. The walkway was flat and no restrictions were imposed on the type of clothes and shoes (none of the participants were wearing shoes with high heels or were using a walking aid).

2) EXTRACTION OF GAIT VELOCITY PARAMETERS

The gait velocity parameters were extracted from the time-velocity distribution of the signals received by the MDR corresponding to one walking cycle in steady state [23], [24]. First, the variation in the velocities of body parts with time was determined by obtaining the short-time Fourier transform (STFT) [21] of the received signals. The signal $s(t)$ was received during the MDR gait measurement, and its STFT spectrogram $|S(t, \Delta f)|^2$ was calculated, where t is time and Δf is the Doppler frequency. The Hamming window function, which has a length of 128 samples (213 ms) was empirically used for the STFT process. The Doppler velocity v is calculated with the Doppler frequency Δf as $v = c\Delta f/(2f)$, where c is the speed of light and $f = 24$ GHz is the frequency of the transmitting signal. Thus, we have the time-velocity distribution $|S(t, v)|^2$ corresponding to the walking motion of the participant. Fig. 3 shows an example of the time-velocity distribution of a walking participant. This figure shows gait features such as the relatively large velocity corresponding to the forward motion of the legs in the swing phase.

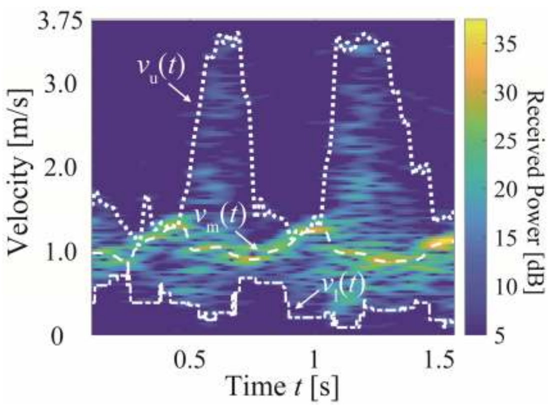

FIGURE 3. Representative spectrogram of MDR signal of a walking participant and extraction results of the envelopes.

We extracted the gait velocity parameters listed in Table 1 from the value of $|S(t, v)|^2$ of one walking cycle in steady state. Similar to previous studies [23]–[25], the upper envelope $v_u(t)$ is extracted as the significant peaks of $|S(t, v)|^2$ corresponding to the maximum v in each t. and the power-weighted mean velocity $v_m(t) = \int v\ |S(t, v)|^2\ dv\ / \int |S(t, v)|^2\ dv$ is also extracted (see Fig. 3). These values correspond to the velocities of the forward motion of the legs in the swing phase and body oscillation during walking, respectively [23], [25]. In addition, this study also extracts the lower envelope $v_l(t)$ as the significant peaks corresponding to the minimum velocity in each period of time (see Fig. 3), and this envelope corresponds to the motions of the legs in the stance phase. Using these envelopes, we calculated the gait velocity parameters defined in Table 1.

TABLE 1. List of extracted gait velocity parameters using MDR.

Para.	Definition	Meaning
$v_{m,mean}$	E[$v_m(t)$]	Mean walking velocity
v_{max}	MAX[$v_u(t)$]	Maximum leg velocity
$v_{u,mean}$	E[$v_u(t)$]	Mean leg velocity in swing phase
$v_{u,std}$	STD[$v_u(t)$]	Degree of variation of leg velocity in swing phase
$v_{l,mean}$	E[$v_l(t)$]	Mean leg velocity in stance phase
$v_{l,std}$	STD[$v_l(t)$]	Degree of variation of leg velocity in stance phase

E[ ], STD[ ], and MAX[ ] indicate the mean, standard deviation, and maximum value with respect to time t respectively.

D. STATISTICAL ANALYSIS

We statistically analyzed the relationships between the extracted gait velocity parameters and the four cognitive function tests. The Pearson's correlation coefficients r of the extracted parameters and the DSST score were calculated to investigate their relationship. For the other tests (MMSE, SPMT, and VFT), the p-values of Welch's t-test were calculated to investigate the statistic difference of the estimated gait parameters between the high- and low-score groups of each test. The significance level was set at $\alpha = 0.05$. An effect size, Hedge's g, was calculated to evaluate the magnitude of the differences. Based on [33], we judged that $g > 0.8$ indicates a large difference among the two groups.

Further, to investigate the possibility of the classification of the score groups in in the MMSE, SPMT, and VFT, the classification rate in a leave-one-out cross validation was also evaluated by using a support vector machine (SVM) [34]. The gait parameters that indicate the significant differences among two groups were selected as the feature parameters in the SVM. The SVM used a Gaussian kernel function, which is known as a general-purpose function. The parameters of the SVM processing were optimized by grid search.

On the basis of all the results, we discuss the gait velocity parameters associated with each cognitive function test. In other words, we aim to reveal the features of the gait deterioration corresponding to each cognitive domain and the global cognition.

III. RESULTS

Table 2 contains the results for the correlation coefficients of the gait velocity parameters and the DSST score and their p-values. Fig. 4 shows the relationship between $v_{m,mean}$, $v_{u,mean}$, and the DSST score of all participants. Significant correlations were found in $v_{m,mean}$, v_{max}, $v_{u,mean}$, and $v_{l,std}$. $v_{u,mean}$ indicated the largest correlation. No significant correlations were found in $v_{u,std}$, and $v_{l,mean}$.

TABLE 2. Results for DSST.

	r	p (*: p< 0.05)
$v_{m,mean}$	0.391	6.95×10^{-4} *
v_{max}	0.351	0.00247 *
$v_{u,mean}$	0.474	2.57×10^{-5} *
$v_{u,std}$	0.101	0.40
$v_{l,mean}$	0.114	0.34
$v_{l,std}$	0.312	0.00762 *

TABLE 3. Results for MMSE.

	High-score (≧24) (Mean ± SD)	Low-score (<24) (Mean ± SD)	p (*: $p < 0.05$)	g (*: $g > 0.8$)
Information of participants				
Number of participants	63 (26 men)	11 (3 men)		
Age (years)	78.6 ± 3.86	81.3 ± 4.92	0.113	
Height (m)	155.2 ± 8.65	155.1 ± 9.08	0.984	
Mass (kg)	54.4 ± 8.24	54.0 ± 5.51	0.871	
Gait velocity parameters				
$v_{\mathrm{m,mean}}$ (m/s)	1.30 ± 0.203	1.08 ± 0.316	0.0445 *	0.98 *
v_{max} (m/s)	3.19 ± 0.308	2.68 ± 0.591	0.0188 *	1.40 *
$v_{\mathrm{u,mean}}$ (m/s)	2.35 ± 0.275	1.84 ± 0.517	0.00866 *	1.58 *
$v_{\mathrm{u,std}}$ (m/s)	0.376 ± 0.0664	0.356 ± 0.0747	0.411	0.29
$v_{\mathrm{l,mean}}$ (m/s)	0.455 ± 0.0923	0.373 ± 0.141	0.0888	0.81 *
$v_{\mathrm{l,std}}$ (m/s)	0.229 ± 0.0464	0.169 ± 0.0611	0.00947 *	1.22 *

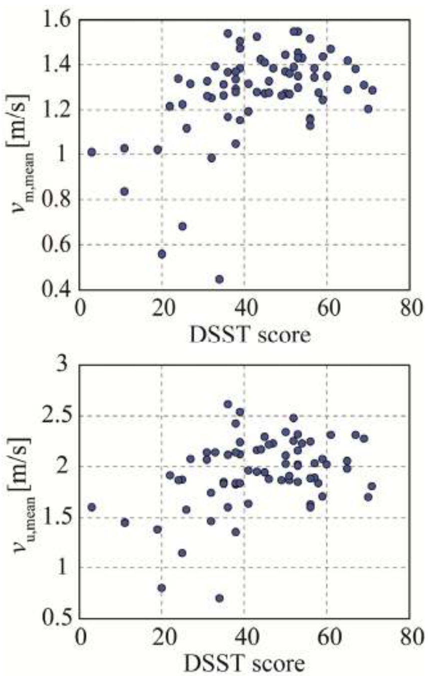

FIGURE 4. Relationship between DSST score and gait velocity parameters for all participants: $v_{\mathrm{m,mean}}$ (above) and $v_{\mathrm{u,mean}}$ (below).

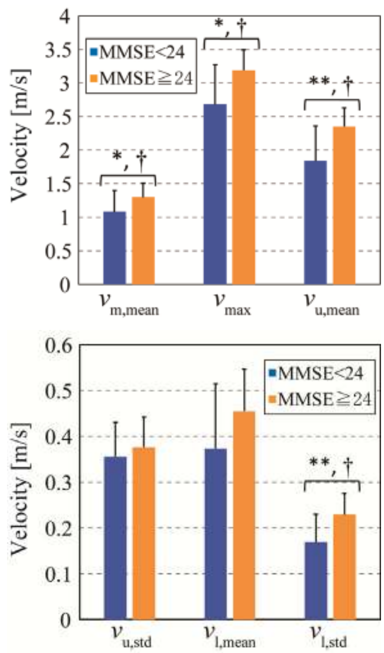

FIGURE 5. Mean and standard deviation of the results of the extraction for the MMSE: ($v_{\mathrm{m,mean}}$, v_{max}, $v_{\mathrm{u,mean}}$) (above) and ($v_{\mathrm{u,std}}$, $v_{\mathrm{l,mean}}$, $v_{\mathrm{l,std}}$) (below). *: $p < 0.05$, **: $p < 0.01$, †: $g > 0.8$.

The results for the MMSE are depicted in Fig. 5 and their detailed values are provided in Table 3. No significant differences were found among high- and low-score groups in age, height, and mass. The values of $v_{\mathrm{m,mean}}$, v_{max}, $v_{\mathrm{u,mean}}$, and $v_{\mathrm{l,std}}$ of the high-score group were significantly larger than those of the low-score group. No significant differences were found in $v_{\mathrm{u,std}}$, and $v_{\mathrm{l,mean}}$. Fig. 6 shows the relationship between $v_{\mathrm{m,mean}}$ and $v_{\mathrm{u,mean}}$ for the high- and low-score groups. Although there is no clear boundary among the two groups, the different tendencies of the groups were confirmed to be significant to some extent.

Fig. 7 and Table 4 show the results of the SPMT. Although no significant differences were found among the two groups in terms of their height and mass, the differences in all gait velocity parameters were significant. However, the effect size of $v_{\mathrm{u,std}}$, is relatively small. Fig. 8 shows the relationship between $v_{\mathrm{u,std}}$, and $v_{\mathrm{l,std}}$, and indicates the relatively clear boundary among the two groups compared with the MMSE results (Fig. 6).

Fig. 9 and Table 5 present the results of the VFT. No significant differences were found among the two groups in terms of their height and mass. The values of v_{max}, $v_{u,mean}$, and $v_{\mathrm{u,std}}$ of the high-score group were significantly larger than those of

TABLE 4. Results for SPMT.

	High-score (≧10) (Mean ± SD)	Low-score (<10) (Mean ± SD)	p (*: $p < 0.05$)	g (*: $g > 0.8$)
Information of participants				
Number of participants	62 (25 men)	12 (4 men)		
Age (years)	78.1 ± 3.00	83.8 ± 6.27	0.013 *	
Height (m)	155.1 ± 8.80	157.2 ± 5.32	0.50	
Mass (kg)	54.1 ± 6.43	58.2 ± 6.43	0.30	
Gait velocity parameters				
$v_{m,mean}$ (m/s)	1.32 ± 0.172	0.993 ± 0.300	0.00204 *	1.64 *
v_{max} (m/s)	3.23 ± 0.245	2.49 ± 0.478	0.000192 *	2.50 *
$v_{u,mean}$ (m/s)	2.39 ± 0.213	1.68 ± 0.426	0.000866 *	2.73 *
$v_{u,std}$ (m/s)	0.381 ± 0.0665	0.332 ± 0.0593	0.0198 *	0.74
$v_{l,mean}$ (m/s)	0.463 ± 0.0800	0.337 ± 0.148	0.014 *	1.33 *
$v_{l,std}$ (m/s)	0.234 ± 0.0380	0.146 ± 0.0584	0.000230 *	2.08 *

TABLE 5. Results for VFT.

	High-score (≧11) (Mean ± SD)	Low-score (<11) (Mean ± SD)	p (*: $p < 0.05$)	g (*: $g > 0.8$)
Information of participants				
Number of participants	63 (24 men)	11 (5 men)		
Age (years)	78.2 ± 3.33	83.4 ± 5.46	0.010 *	
Height (m)	154.8 ± 8.47	159.8 ± 9.92	0.33	
Mass (kg)	54.1 ± 7.93	57.2 ± 9.71	0.53	
Gait velocity parameters				
$v_{m,mean}$ (m/s)	1.29 ± 0.211	1.13 ± 0.316	0.116	0.52
v_{max} (m/s)	3.18 ± 0.335	2.71 ± 0.522	0.0150 *	1.27 *
$v_{u,mean}$ (m/s)	2.34 ± 0.295	1.88 ± 0.486	0.0104 *	1.39 *
$v_{u,std}$ (m/s)	0.382 ± 0.0674	0.327 ± 0.0482	0.00440 *	0.84 *
$v_{l,mean}$ (m/s)	0.444 ± 0.0927	0.437 ± 0.160	0.891	0.05
$v_{l,std}$ (m/s)	0.226 ± 0.0477	0.189 ± 0.0709	0.124	0.54

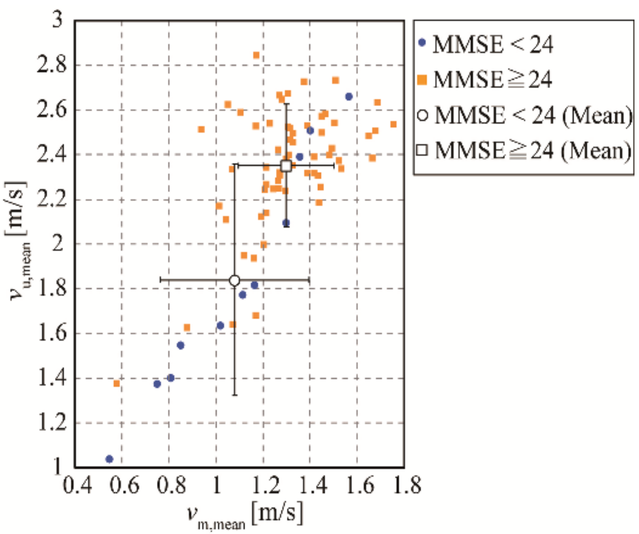

FIGURE 6. Relationship between $v_{m,mean}$ and $v_{u,mean}$ with the label of high-and low-MMSE scores.

the low-score group. No significant differences were found in $v_{m,mean}$, $v_{l,mean}$, and $v_{l,std}$.

Table 6 provides the results of the effectiveness with which each gait velocity parameter is able to evaluate the cognitive function tests. The results of the evaluation of the ability of SVM to classify the high- and low-score groups of MMSE, SPMT, and VFT are provided in Table 7. The classification rate in the SPMT and VFT exceeds 90%, whereas the rate for the MMSE is greater than 85%.

TABLE 6. Summary of parameters associated with each test.

	MMSE	DSST	SPMT	VFT
$v_{m,mean}$	*	†	**	
v_{max}	*	†	***	*
$v_{u,mean}$	**	‡	***	*
$v_{u,std}$			*	**
$v_{l,mean}$			*	
$v_{l,std}$	**	†	***	

For MMSE, SPMT, and VFT, *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$.
For DSST, †: $0.2 < r$, ‡: $0.4 < r$.

IV. DISCUSSION

A. MAIN FINDING OF THIS STUDY

In this study, a simple MDR measurement was used to show that the various gait velocity parameters are more effective to assess cognitive functions than the walking speed.

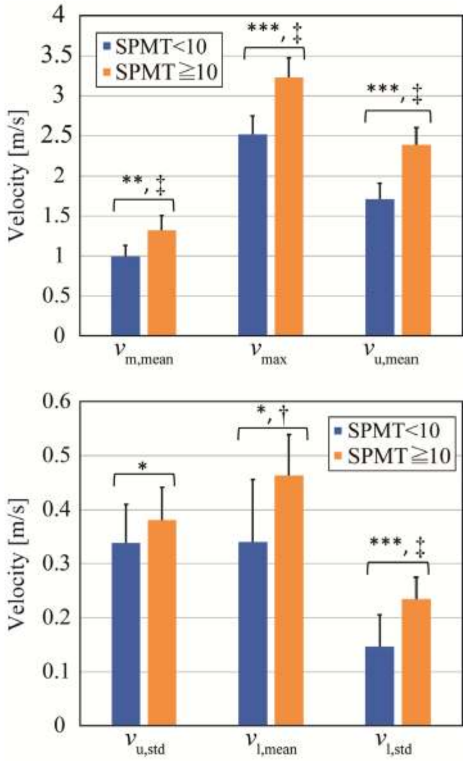

FIGURE 7. Mean and standard deviation of the results of the extraction for the SPMT: ($v_{\mathrm{m,mean}}$, v_{max}, $v_{\mathrm{u,mean}}$) (above) and ($v_{\mathrm{u,std}}$, $v_{\mathrm{l,mean}}$, $v_{\mathrm{l,std}}$) (below). *: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$, †: $g > 0.8$, ‡: $g > 1.6$.

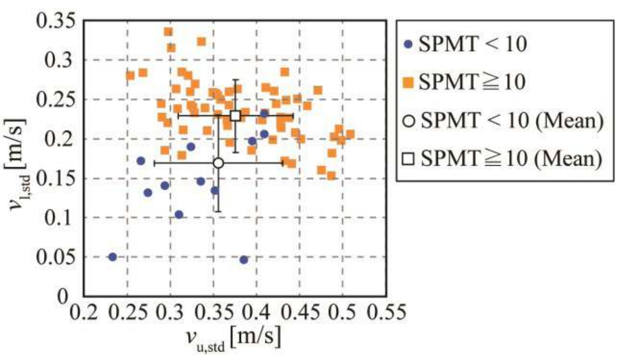

FIGURE 8. Relationship between $v_{\mathrm{u,std}}$ and $v_{\mathrm{l,std}}$ with the label of high- and low-SPMT scores.

TABLE 7. Classification results of high-/low-score groups.

Test	Feature parameter	Classification Rate
MMSE	($v_{\mathrm{m,mean}}$, v_{max}, $v_{\mathrm{u,mean}}$, $v_{\mathrm{l,std}}$)	87.9 %
SPMT	($v_{\mathrm{m,mean}}$, v_{max}, $v_{\mathrm{u,mean}}$, $v_{\mathrm{l,mean}}$, $v_{\mathrm{l,std}}$)	94.6 %
VFT	(v_{max}, $v_{\mathrm{u,mean}}$, $v_{\mathrm{u,std}}$)	90.5 %

Many conventional studies investigated the relationship between cognitive function and walking speed. However, in all tests considered in this study, the results in Table 6 indicate that the gait parameters corresponding to the leg motions

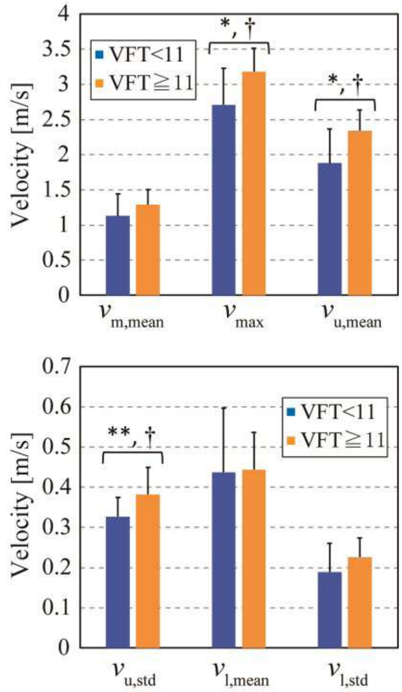

FIGURE 9. Mean and standard deviation of the results of the extraction for the VFT: ($v_{\mathrm{m,mean}}$, v_{max}, $v_{\mathrm{u,mean}}$) (above) and ($v_{\mathrm{u,std}}$, $v_{\mathrm{l,mean}}$, $v_{\mathrm{l,std}}$) (below). *: $p < 0.05$, **: $p < 0.01$, †: $g > 0.8$.

are more significant than $v_{\mathrm{m,mean}}$ which corresponds to the walking speed. These results indicated that extracted gait velocity parameters are effective for the monitoring of cognitive function and the detection of cognitive impairment, dementia, and their signs.

The gait parameters were also found to be associated with each cognitive function test, as indicated in Table 6. For the MMSE and DSST, $v_{\mathrm{u,mean}}$ was the most significant parameter and v_{max}, $v_{\mathrm{m,mean}}$, and $v_{\mathrm{l,std}}$ were also significant. Significantly smaller $v_{\mathrm{l,mean}}$ and $v_{\mathrm{u,std}}$ values are confirmed for the low-score group of the SPMT. The VFT results were characteristic because $v_{\mathrm{u,std}}$ indicated significance, but was not significant for the MMSE, DSST, and SPMT. These results show that we are not only able to detect cognitive impairment, but it is also possible to identify the specific cognitive domain that has deteriorated. Existing evidence suggests there are distinct cognitive decline patterns across syndromes, such as Alzheimer's disease and vascular dementia, which may help differential diagnosis [35]. Thus, identification of the deteriorated domain makes it possible to provide the necessary assistance and care and to prevent disease related to cognitive impairment.

Furthermore, for the MMSE, SPMT, and VFT, the classification of low- and high-score groups was achieved using the SVM, and the classification rates are presented in Table 7 (Note that the accuracy with the other classifiers (random forest, nearest neighbor, and neural networks [36]) was either the same or low compared with these results.). These results indicate the possibility of detecting cognitive impairment via the extracted parameters. However, the number of participants in the low-score groups of all tests was insufficient to verify the classification capability. Thus, further investigation by using additional participants would be necessary to verify the classification of participants with cognitive impairment with sufficient accuracy.

B. MERITS OF OUR MDR TECHNIQUE

Another important finding of this study was that the above efficient gait velocity parameters were extracted from the MDR measurements unconstrained and in real time with a low-complexity system. As indicated in Fig. 2, the physically small MDR can record the gait information without any need for the subjects to wear sensors. In addition, subjects' clothes did not pose a restriction, installation of a large-sized system or construction of complicated sensing environments was unnecessary, and assistance from specialists such as physiotherapists was not required. Furthermore, in contrast to conventional sensing systems, the velocity parameters of leg and foot motions were easily extracted. The proposed method only required signals corresponding to one walking cycle (approximately 1 s) to extract the gait velocity parameters for each participant. In addition, the processing time for the extraction of the gait parameters is less than 0.01 s (processor: Intel Core i5-7300U CPU @ 2.60 GHz 2.71 GHz) because they are calculated using simple STFT and envelope detection processes. Thus, MDR gait measurement is applicable to monitoring cognitive functions on a daily basis.

C. REASON FOR AND MECHANISM OF OUR RESULTS

Next, we discuss the reason why the extracted parameters are associated with the cognitive function. Previous studies verified that the walking speed was closely related to DSST scores [8]–[10], and is consistent with the results shown in Fig. 4 in this paper. This can be explained by the extent to which the prefrontal cortex is activated. This cortex is reported to be a common area interlinking walking and the cognitive domain of processing speed [9] and this might be the reason for the relationship between the DSST score and the extracted gait parameters. Our previous research on MDR gait measurement [23] showed that the gait velocity parameters are correlated to each other. In [16], cadence is also related to the processing speed for the same reason. A significant relationship between cadence and leg and foot motions in the swing phase is known to exist and has been verified [37], [38]. Thus, it seems that the correlations between the DSST score and $v_{\mathrm{u,mean}}$ and the other parameters were significant.

A similar discussion about the relationship between walking ability and short-term memory was noted [10], [14]–[17]. In [14], it was reported that the short-term memory ability is also related to the prefrontal cortex during motor activity. Thus, the tendency displayed by the results of the SPMT was the same as that for the DSST (Table 6). However, different from the DSST, $v_{\mathrm{l,mean}}$ and $v_{\mathrm{u,std}}$ were also associated with the SPMT score. Verghese *et al.* [16] reported that not only the walking velocity but also the rhythm factor in walking, which is calculated from the cadence and the time required for both the swing and stance, are associated with the memory ability of elderly adults. Hence, the swing time and stance time are related to the velocity parameters. In addition, there is no strong evidence of associations between the walking rhythm and cognitive domains other than the memory [6]. Thus, we can predict that the walking rhythm is significantly related to all parameters.

For the VFT, the walking velocity did not indicate significant differences. Actually, the number of studies reporting a significant relationship between the VFT and walking speed is relatively small [6]. However, v_{max}, $v_{\mathrm{u,mean}}$ and $v_{\mathrm{u,std}}$ were significant in our results. Soumare *et al.* [11] reported that the VFT results indicated significant differences between the groups with the highest and lowest maximum walking speed, where the maximum walking speed is defined as the walking speed of a participant who is instructed to "walk as fast as you safely can." The maximum walking speed seems to be related to the motor ability of the legs and is thus related to the velocity parameters of the swing phase. Furthermore, an important feature of the results of the VFT is the significance of $v_{\mathrm{u,std}}$, which was ineffective in other cognitive tests. Our previous research found that $v_{\mathrm{u,std}}$ can be used to classify subject groups with different balancing ability [23]. In addition, it was reported that the VFT score is improved by physical exercise [31], [32]. This implies that the executive function associated with the VFT is related to physical activity. The balance ability was also reported to be related to the level of physical activity [39], [40]. Thus, we can predict that these associations are responsible for those between the VFT scores and the relationship between the gait velocity parameters and the balance ability.

Finally, we discuss the results for the MMSE. In our results in Table 6, the parameters associated with the DSST and the SPMT results also indicated significant differences for the MMSE results. However, the significance level of the parameters associated with the MMSE is smaller than that of the same parameters in the SPMT results from the viewpoint of both the p-value and the effect size g. Additionally, there is no clear difference in the MMSE results of all subjects as shown in Fig. 6, contrary to the clearly correlated results of the DSST in Fig. 4. Based on these results, although the decline of the global cognition also leads to statistical deterioration of the gait, the degree of association with the gait parameters is small compared with the results for the DSST and the SPMT, which assess each cognitive function. This is because the MMSE results reflect global cognition, which is composed of different cognitive domains [1]. As discussed above, the processing speed and memory functions are closely related to the gait velocity parameters $v_{\mathrm{m,mean}}$, v_{max}, $v_{\mathrm{u,mean}}$, and $v_{\mathrm{l,std}}$. However, the language and executive function domains that are assessed by the VFT did not indicate large significance for these parameters. Because these cognitive domains resort under global cognition, we can consider the MMSE to provide a comprehensive indication of the results of other cognitive tests and this is the basis for our results. The above discussion is consistent with the results of conventional studies [11], [13], which also revealed little association between the MMSE and the walking speed compared with tests of other cognitive functions.

D. LIMITATIONS OF THIS STUDY

This study has three limitations. The first is the small number of participants, as discussed in Section IV-A. However, the results were significant to some extent.

Second, the measurement situation is limited. Our experiment involved a single pedestrian. However, for daily monitoring in homes and hospitals, the system requires the capability to measure multiple pedestrians walking in an arbitrary direction. However, our other studies demonstrated applications of the MDR to measure the velocity of a pedestrian moving in a diagonal direction [26] and successfully separated the measurements of two pedestrians [29]. Thus, the technique we presented here could be extended by combining it with our previously proposed methods to enable MDR gait measurement for cognitive function assessment to become ubiquitous and this is our important future task.

Another important limitation is that the considered cognitive domain is limited to that shown in Fig. 1. Thus, evaluations of the relationships between the gait parameters and the test results of other cognitive functions are required to more accurately assess the cognitive functions and to determine the mechanism of the association between gait and cognitive function in more detail.

V. CONCLUSIONS

This study showed that the MDR-measured gait velocity parameters are associated with the various cognitive domains and global cognitive function of elderly participants aged 75 years and older. The results verified that it is not only the walking speed that is indicative of the cognitive function, as was mainly considered in previous studies. In addition, we showed that various other velocity parameters corresponding to leg motion indicated significant relationships to the cognitive function tests and could be used to classify high- and low-score groups in each test. Furthermore, these parameters were extracted by using a low-complexity MDR system combined with signal processing with a low computational load. Thus, MDR is a promising candidate for the daily unconstrained monitoring of cognitive functions. Future work is required to remove the limitations described in Section IV-D to develop a practical monitoring system. Additionally, the identification of other effective gait parameters obtained with other processing techniques and/or by increasing the small number of MDRs might be important to improve the accuracy of the assessment and screening of cognitive impairment.

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