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Early Detection of Lower MMSE Scores in Elderly Based on Dual-Task Gait

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ABSTRACT The dual-task paradigm is a promising procedure for estimating cognitive status and may also be collaterally used to reduce cognitive decline and prevent dementia. In this paper, we use the mini-mental state exam (MMSE) to the assess cognitive status in the elderly as a reference and investigate the potential of using machine learning for early detecting cognitive impairment in the elderly. Although many studies have suggested that dual-task performance, in which participants perform a cognitive task while walking, is associated with cognition, they only considered the correlation between cognitive parameters and simple gait feature, such as gait speed, through the statistical analysis. We instead use a Kinect sensor to capture participants' whole-body movements and extract a rich gait feature that has the ability to exhibit different tendencies of movements between healthy and cognitive-impaired elderlies. In our experiments, a classifier based on the dual-task gait feature achieved a higher performance than the one based on the single-task feature; the performance of the rich gait feature was better than that of a simple one, and; an optimal detection performance was achieved with an MMSE cutoff score of 25. We positively validated that the proposed method could early detect elderly with lower MMSE scores based on dual-task gait feature with a promising performance. Our approach can support early and automated diagnosis of cognitive impairment.

INDEX TERMS Cognitive impairment, dual-task, elderly, machine learning, signal processing.

I. INTRODUCTION

Dementia is one of the major causes of disability in later life. According to the World Health Organization, the number of people living with dementia worldwide was estimated at 47 million by April 2017 and is projected to increase to 75 million by 2030. The number of cases of dementia are estimated to almost triple by 2050 [1]. The principal goals for dementia care include early diagnosis, as well as detecting and treating behavioral and psychological symptoms [2]. Because no disease-modifying treatments are currently available, a demand for effective strategies for preventing dementia is increasing [3]. Cognitive decline may be reduced by aerobic exercise [4], [5], including walking [6], according to epidemiological cohort studies. In this research, we tackle an early diagnosis of cognitive impairment based on dual-task gait performance.

Lundin-Olsson *et al.* showed in their seminal work [7] that older adults who stopped walking when talking exhibited less safe gait, slower mobility performance, and increased dependence in activities of daily living. Associations between cognitive and gait performance in older adults have been suggested by several studies [8]–[10], and gait impairment or decline have been considered to be possible predictors of cognitive impairment [11]–[15]. Control over gait and posture is no longer considered an automatic task, but rather an attention-demanding one [16]–[18]. Based on these studies, an underlying assumption for the dual-task gait assessment is that when walking and an attention-demanding task are simultaneously performed, the performance

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in either or both tasks can deteriorate because processing capacity is limited.

Many studies have suggested that dual-task gait performance is associated with cognition [19]–[21]. Using dual task to assess cognition is promising because dual-task assessment is less influenced by educational level and is functional, fast, and easily applicable in clinical practice [22]. However, only simple gait parameters were used with simple statistical models to carry out a diagnosis of cognitive impairment. In these work, basic gait parameters, such as gait speed, step time, step length, support base, and double support phase, were obtained in different ways by different studies. These parameters were fed into a statistical analysis to investigate the correlation to cognitive status as assessed by a test, such as the Mini-Mental State Exam (MMSE) [23] or Trail Making Test (TMT) [24]. However, this small number of parameters may be insufficient not only to assess associations between cognitive and gait performance but also to estimate the cognitive impairment of participants who actually tend to be highly variable in their gait performance, especially in the case of a large sample size.

Recent gait studies have used the Microsoft Kinect sensor [25]–[29] to take the advantage that the whole-body movement can be modeled in 3D. A depth-sensing camera allows the Kinect to extract the 3D positions of human body joints in a two-stage process: a depth map is constructed using time-of-flight technology, and then the pose of a user's body can be inferred, such as by a machine-learning approach [30]. Compared with conventional motion analysis systems, which are expensive and require large spaces, the Kinect sensor is so affordable and portable that it can be used in homes and elderly facilities.

In this paper, we investigate an ability to detect lower MMSE scores among the elderly using their dual-task gait feature extracted via a Kinect sensor, which can lead to a detection of cognitive impairment. The elderly with lower MMSE scores may have a tendency to behave differently from those who are healthy, especially while performing dual tasks. Such a tendency may be exhibited by a whole-body gait feature. In this way, we extract a rich gait feature by applying a time-frequency analysis to a time series of 3D coordinates of body joints. Machine-learning algorithm is then used to distinguish a cognitive impaired elderly from normal healthy ones. The main contributions of this work are summarized as follows:

- We propose a quick and automatic solution that detects lower MMSE scores among the elderly based on their dual-task gait feature.
- We suggest a signal-processing method for gait feature extraction with Kinect sensor and an associated machine-learning technique.
- We compare dual-task gait feature with single-task gait feature in terms of accuracy in detecting elderly with a lower MMSE score.
- We investigate an optimal MMSE cut-off score and the contribution of individual body parts.

The remaining of this paper is organized as follows. Section II describes participants, dual tasks that the participants performed, and measurement of dual-task performance. Section III describes gait feature extraction method. Section IV presents and discusses the experimental results. Finally, conclusions are stated in Section V.

II. PARTICIPANTS AND DATA ACQUISITION

The sample dataset consists of 27 males and 76 females who were recruited from the users of health care facilities for the elderly. Most participants (63) were aged between 68 and 90 years, while remaining ones did not release their ages. The distribution of genders by age is shown in Fig. 1. All the participants completed the MMSE [23] and released their MMSE scores. The MMSE includes a series of questions and instructions that aim to assess people's orientation, memory, attention, recall, and language abilities. The maximum total score is 30 and the most frequently used cut-off score to indicate the presence or absence of dementia is 24 [31], [32]. We adopt the MMSE as the gold standard to find the tendency of cognitive impairment.

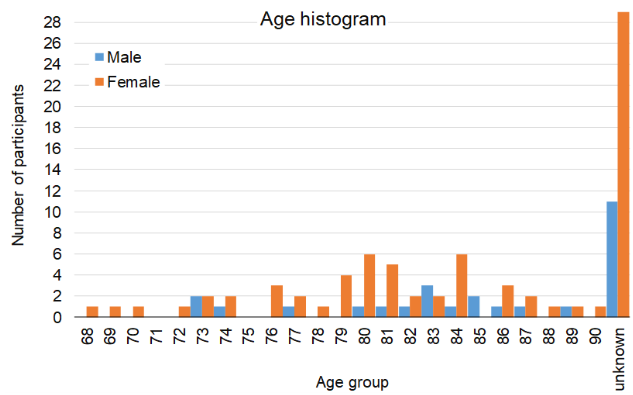

FIGURE 1. The distribution of genders by age.

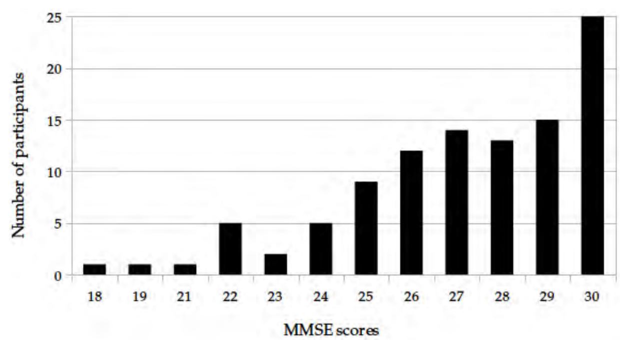

FIGURE 2. The distribution of participants MMSE scores ($n = 103$).

Fig. 2 shows the distribution of participants' MMSE scores. The large difference in number between the two groups of participants separated by a cut-off score can cause negative effects on the classification performance of machine-learning algorithms because trained classifiers are biased towards the majority class. To address the difficulties, a discriminative representation for classification should be acquired.

A dual task involves walking with a cognitive-loading condition. We instructed the participants to walk in one spot to measure the positions of body joints by Kinect. The participants performed the following tasks while walking in place for 1 minute: (1) a dual task of serial ones (counting down from 100 by ones) [20], and (2) a single task without cognitive load.

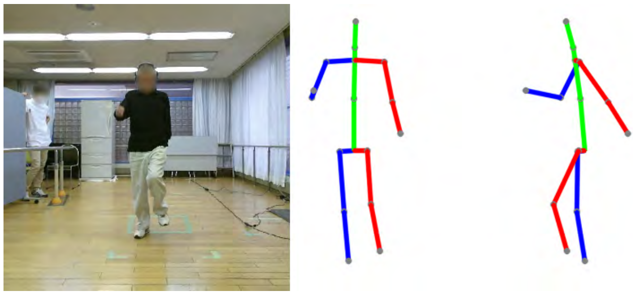

FIGURE 3. Data acquisition and body joints.

Gait was captured by a Kinect sensor, as shown in Fig. 3. Whole-body movements were obtained as a time series of coordinates of body joints. We extracted gait feature from these measurement data, as described in the next section.

III. GAIT FEATURE EXTRACTION

To detect older adults with lower MMSE scores, we used a linear support vector machine (SVM) model [33] as a classifier which was trained based on gait feature.

Although single-task gait parameters such as step time can be associated with cognitive impairment, they are insufficient for classifying participants through their dual-task performance because elderly people are typically unable to maintain the rhythm and magnitude of their movements [34]. This is especially the case when performing dual tasks. Moreover, such a fluctuation in an individual cannot be represented. We used the Kinect sensor to measure participants' whole-body movements, which were separated into sequences of coordinates of body joints, as shown in Fig. 4.

While we can observe a participant's movements in detail through measurement data, investigating and understanding associations between their cognitive impairment and the measurement data is difficult. Difficulties in analyzing measurement data can be caused by individual differences, nonlinearity, and nonstationarity. A suitable physical feature should be extracted from the data to exhibit different movement tendencies in participant groups separated according to their cognitive performance.

We adopted the Hilbert-Huang transform (HHT) [35], which is designed for analyzing a time series of data that can be nonlinear and nonstationary. The HHT consists of the empirical mode decomposition (EMD) [36] followed by the Hilbert transform. The EMD has been used to classify electroencephalogram (EEG) signals, which are nonlinear and nonstationary in nature, with high accuracy [37].

According to the EMD, data may have a finite and often small number of coexisting simple oscillatory modes of significantly different frequencies, one superimposed on the other. Each component is called an intrinsic mode function (IMF) and satisfies the following conditions: (1) The difference between the number of extrema and the number of zero crossings is less than or equal to one for the entire time series. (2) The mean value of its upper and lower envelopes equals zero at any time. Thus, an IMF is almost symmetrical and has a unique local frequency. The movements of body joints as a time series of data do not commonly satisfy these conditions which admit well-behaved Hilbert transforms. Fig. 5 shows the results of the EMD, i.e., intrinsic mode functions, applied only to the X coordinate of the data shown in Fig. 4, due to space limitations. The signals corresponding to relatively stable body parts, such as the head, shoulders, and spine, tend to be decomposed into a smaller number of IMFs. Conversely, the signals obtained from parts whose movements are not stationary, for example the knees, should be decomposed into a greater number of IMFs.

With the Hilbert transform, the IMFs yield instantaneous frequencies as functions of time. The HHT can deal with nonlinearity and nonstationarity better than the traditional paradigm of constant frequency and amplitude. The final result is a time-frequency-energy distribution, designated as the Hilbert spectrum. Fig. 6 depicts the results of the HHT for all the data shown in Fig. 4. Focusing on the X coordinates, which correspond to movements perpendicular to the floor, the power of high frequency bands appear in the spectrum of the knees, ankles, and wrists. However, they do not appear in the spectrum of other body parts such as the head, shoulders, and spine. From the spectrums, we can observe which body parts moved to a greater extent than other body parts; for this participant, the knees, ankles, and wrists moved to a greater extent than the head, shoulders, and spine.

As shown in Fig. 7, compared with continuous wavelet analysis, a spectrum obtained using the HHT gives a sharper frequency resolution. The energy distribution in the time-frequency domain in the HHT can be regarded as a skeleton form of that in continuous wavelet analysis [35].

To extract a feature robust against a small fluctuation, we first divide the Hilbert spectrum into $k \times l$ blocks, where k and l are the number of intervals along the horizontal axis (frame) and the vertical axis (frequency), and are set experimentally to $k = 3$ and $l = 160$, respectively. Then we aggregate amplitudes (or energy) within each block, which yields a $3 \times 160 \times 51 = 24,480$ dimensional feature because we measured three-dimensional coordinates of 17 body joints. Furthermore, to reduce the number of dimensions and to make the feature more robust to noise, we apply principal component analysis (PCA) and use a p-dimensional vector produced by using only the first p loading vectors as a physical feature for each participant. A optimal parameter of p is set by experimentation.

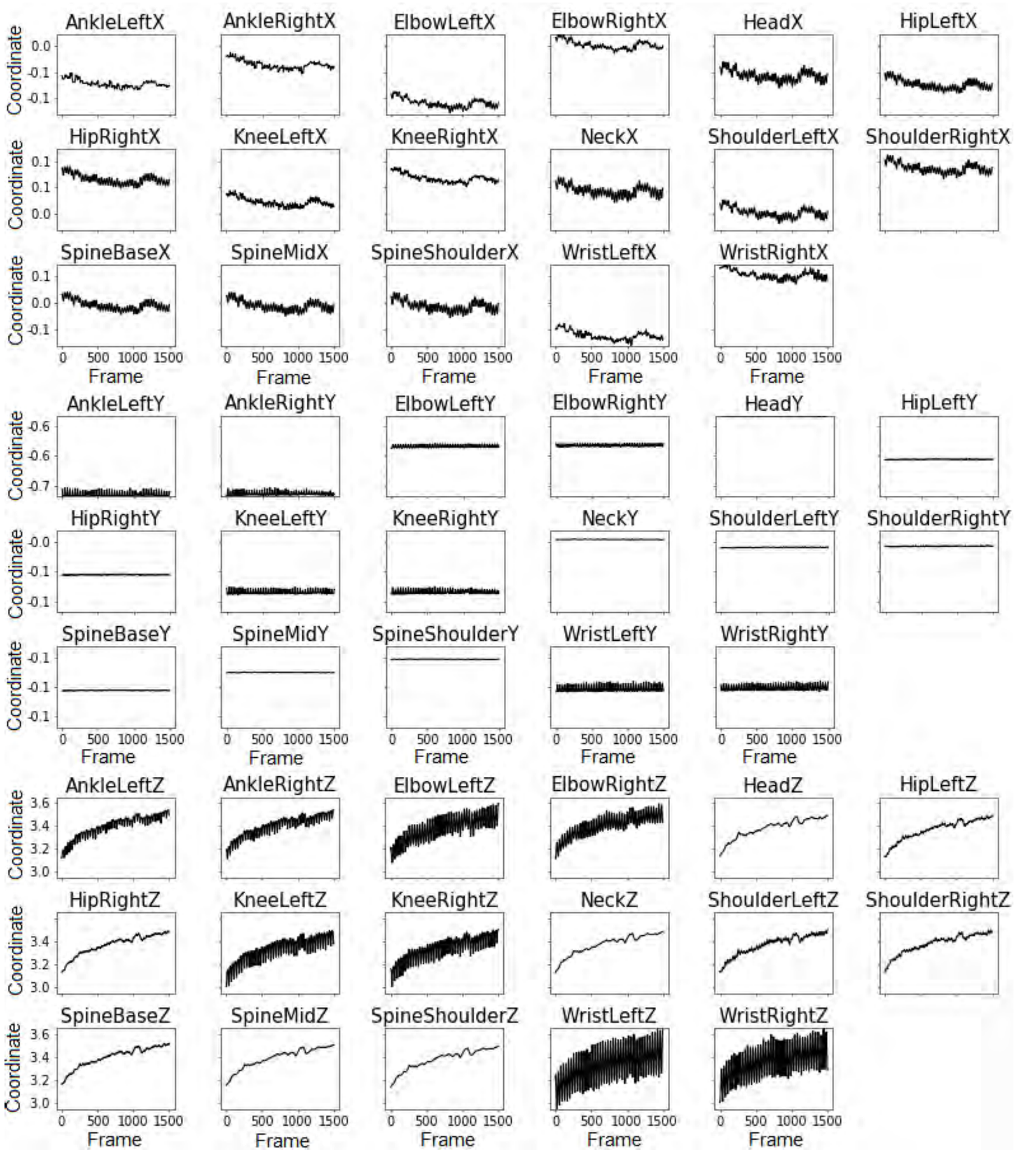

FIGURE 4. Measured coordinates of a participant's body joints. X coordinates correspond to movements perpendicular to the floor, and the plots indicate the participant's change in behavior over time.

IV. RESULTS AND DISCUSSION

In our experiments, we first explored the optimal MMSE cut-off score; then compared the performances of the single-task gait feature versus the dual-task one; compared the performances of proposed and the simple gait features at the optimal cut-off score; and finally, investigated the importance of body parts by an ablation study. A cut-off score is defined as follows. With a specified cut-off score, participants are split into two groups according to their MMSE scores; those with a score less than the cut-off score are classified as positive, and those with a score greater than or equal to the cut-off score are classified as negative.

We repeated the 5-fold cross-validation procedure 200 times with linear support vector machine (SVM). Stratified sampling was used so that relative class frequencies were approximately preserved in each training and test fold. For each training set, we applied an exhaustive grid search to choose optimal hyper-parameters of a classifier from candidate parameters. To evaluate the classification performance of our approach, we adopted a receiver operating characteristic (ROC) curve where sensitivity was plotted against $1 -$ specificity, and where the area under the curve (AUC) was used [38]. A total of 1000 ROC curves was obtained via cross-validation and averaged into a curve for performance evaluation.

A. EXPERIMENT AGAINST MMSE CUT-OFF SCORES

We first sought the optimal parameter of p by fixing the cut-off score at 25 and checking detection performances (AUC) against different parameters of p. The experimental result is summarized in Fig. 8. From the graph, the best detection

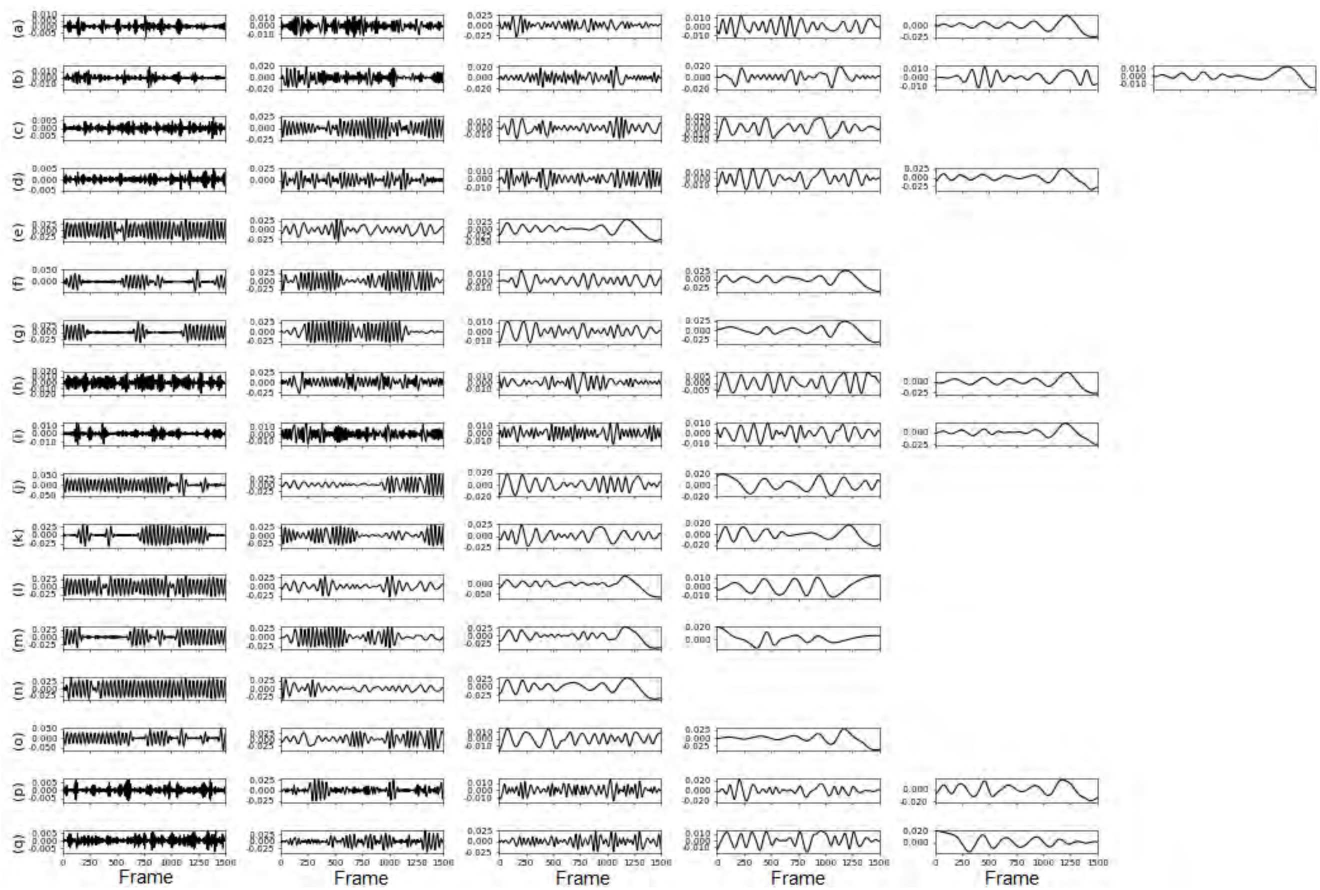

FIGURE 5. The intrinsic mode functions of the X coordinates in the data shown in Fig. 4. (a) AnkleLeft, (b) AnkleRight, (c) ElbowLeft, (d) ElbowRight, (e) Head, (f) HipLeft, (g) HipRight, (h) KneeLeft, (i) KneeRight, (j) Neck, (k) ShoulderLeft, (l) ShoulderRight, (m) SpineBase, (n) SpineMid, (o) SpineShoulder, (p) WristLeft, (q) WristRight.

TABLE 1. Comparison among cut-off scores.

Cut-off score	24	25	26	27	28
Positive participants	10	15	24	36	50
Negative participants	93	88	79	67	53
AUC	0.631	**0.747**	0.556	0.586	0.472

performance was found at $p = 20$. Therefore, we employed this optimal parameter for p in the remaining experiments.

We then conducted the experiment to compare the classification performance against cut-off scores for the MMSE. Fig. 9 shows the corresponding ROC curves. Each cut-off score split participants into two groups as shown in Table 1. The largest AUC was achieved when participants were split according to a cut-off score of 25. The second-largest AUC was achieved by a cut-off score of 24, which is widely considered as the standard cut-off score for realizing healthy and cognitive-impaired. The AUC values with cut-off scores of 26, 27, and 28 were dominantly smaller than that with cut-off score of 25. Since the optimal cut-off score is 25, our method has a capability of early detection of cognitive impairment in comparison with the widely-used cut-off score of 24.

The optimal cut-off score of 25 suggested from our experiments is also comparable to those in the literature [31], [32], while Tombaugh and McIntyre [39] demonstrated that no single cut-off score serves all purposes, and Nasreddine *et al.* [40] noted no optimal single score for the MMSE. A conclusion drawn from our observations is that differences in dual-task performance between those with cognitive impairment and those who are healthy allows for the use of signal-processing and machine-learning techniques to detect lower MMSE scores in the elderly.

B. COMPARISON BETWEEN DUAL- AND SINGLE-TASK GAIT FEATURES

We conducted an experiment to compare the classification performance between single- and dual-task gait features. In this experiment, the cut-off score for the MMSE was set at the optimal cut-off score, which split participants into two groups of 15 positive and 88 negative participants. Single-task gait feature was extracted from the single-task walking in place, while dual-task gait feature were extracted from dual-task walking in place while performing cognitive task.

As shown in Table 2, the performance of dual-task gait feature is much better than that of single-task feature.

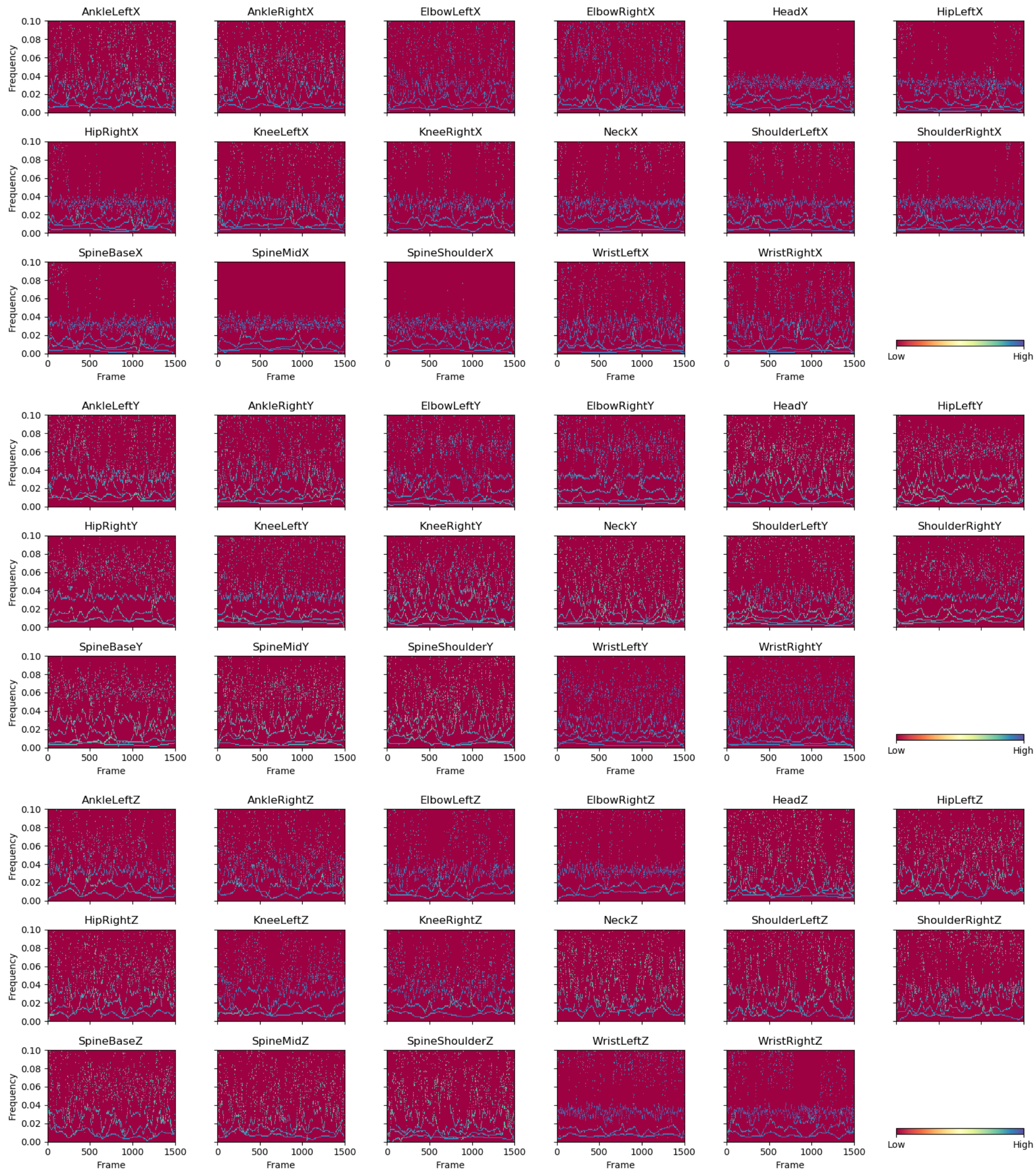

FIGURE 6. The Hilbert spectrum in log-scale obtained by applying the Hilbert-Huang transform to the data shown in Fig. 4.

TABLE 2. Comparison of areas under the ROC curves among features.

Single-task gait.	Dual-task gait.
0.598	**0.747**

The corresponding ROC curves are shown in Fig. 10. We can conclude from the comparison that the feature extracted from the dual-task measurement can better discriminate than the feature extracted from the single-task measurement.

C. COMPARISON BETWEEN SIMPLE- AND RICH-GAIT FEATURES

We conducted an experiment to show the advantage of the proposed (rich) gait feature over a conventional simple feature also at the optimal cut-off score of 25. We extracted a simple gait feature as follows:

1) A set of local minima and maxima (peaks) was detected from each sequence of coordinates of body joints.
2) A time duration between two peaks was defined as motion speed, and a difference between two peaks was defined as motion magnitude.
3) A coordinate sequence was divided into three blocks, and for each block, motion speed and magnitude were averaged.

Thus, we obtained three parameters from the motion speed and magnitude of three coordinates of 17 body joints, which totaled 306 parameters. In the same way as the rich gait feature, we used the first 20 loading vectors obtained by PCA.

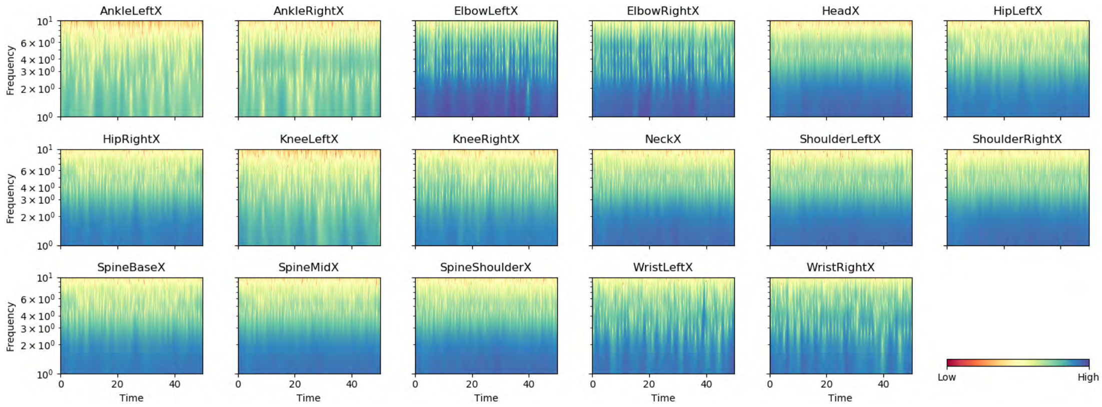

FIGURE 7. The wavelet spectrum in log-scale of the data shown in Fig. 4. In comparison with Fig. 6, the Hilbert spectrum gives a much sharper resolution, seen as higher contrast, in frequency than the wavelet spectrum.

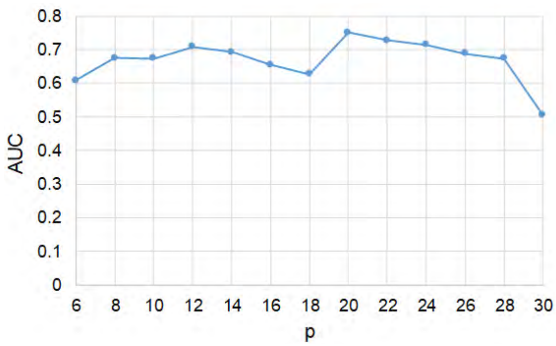

FIGURE 8. Comparison of detection performances against different parameters of p. The best performance is found at $p = 20$.

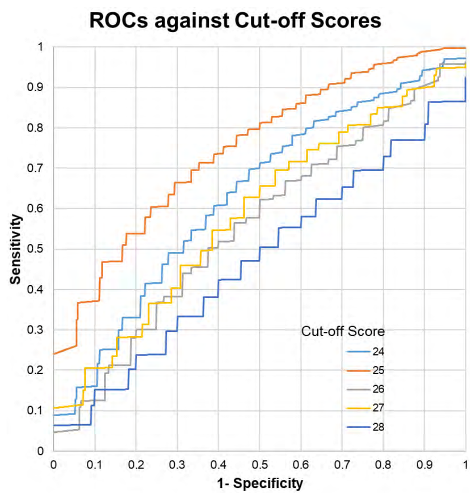

FIGURE 9. Comparison of ROC curves against cut-off scores.

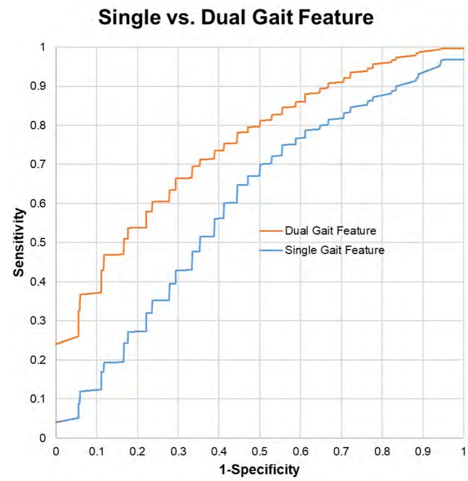

FIGURE 10. Comparison of ROC curves among features.

TABLE 3. Comparison between simple and rich (proposed) gait features during a dual task.

Gait parameters	Simple	Rich
AUC	0.666	**0.747**

This simple feature imitates single-task gait parameters usually used in previous studies, but can represent participant's movements more expressively.

We compared rich gait feature with simple one extracted from the dual-task measurement. As shown in Table 3 and Fig. 11, the proposed rich gait feature based on the HHT could discriminate better than the simple gait feature could do.

D. COMPARISON AMONG BODY PARTS

Finally, we conducted an experiment to investigate the importance of body parts by an ablation study. In other words, we alternatively excluded gait signal of head, neck, spine, wrists, elbows, shoulders, hips, knees, and ankles and investigated the corresponding detection performances (by AUC). The experiment is summarized in Fig. 12. From the figure, we see that the best performance was obtained when shoulder joints were excluded (e.g., AUC $= 0.772$). This improvement can be explained by the fact that motion of shoulders was weak and not intentional and hence was considered as noise. As a result, the exclusion of shoulders motion slightly improved the detection performance. Similarly, motion of participant's head was unrestricted and depended on spontaneous participant's eye gaze and hence the exclusion of

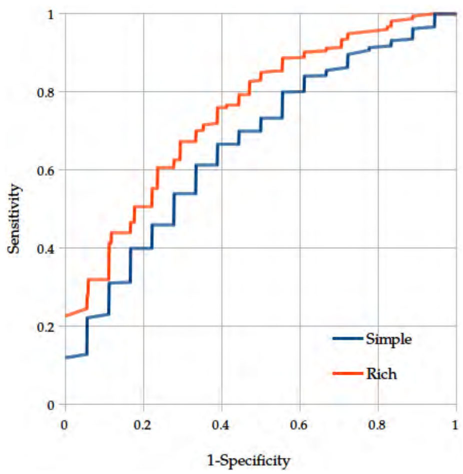

FIGURE 11. Comparison of ROC curves between simple- and rich-gait features.

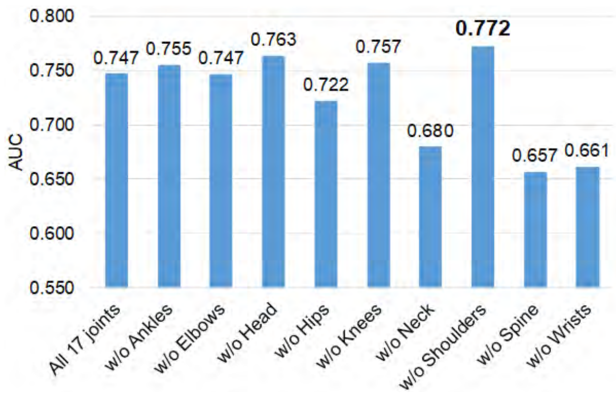

FIGURE 12. Ablation study on the impact of body parts.

head motion also slightly improved the detection performance (e.g., AUC = 0.763). On the other hand, motion of participant's knees was intentional and usually strong, however, it depends on the participant's physical strength more than on cognitive impairment and hence the exclusion of the knees motion did not influence the detection performance. In contrast, the exclusion of motion of participant's spine, wrist, or neck significantly reduced the detection performance (e.g., AUC = 0.657, 0.661, and 0.680, respectively) as these body parts played key roles in detecting cognitive impairment.

V. CONCLUSION

We demonstrated the classification of older adults based on their dual-task gait feature and achieved reasonable performance. Dual-task gait feature was extracted from the measurement data while walking in place with a cognitive-loading condition. Specifically, using the Kinect sensor, whole-body movements of a participant were measured as a time series of coordinates of the body joints. The HHT was employed to extract a high-dimensional gait feature from the time series data and classifier was trained with linear SVM models. In the experiments, we found that an optimal detection performance was obtained at a cut-off score of 25, which enables a capability of early detection of cognitive impairment. Further, we also verified that dual-task gait feature is much more effective than that of single-task one.

In current study, we obtained promising results using only dual-task gait feature. This is beneficial for medical doctors to quickly diagnose the cognitive impairment at a very beginning stage. However, during a dual task, cognitive performance is also important in detecting cognitive impairment. Moreover, different elderlies may prioritize tasks differently depending on their physical and cognitive conditions [41]–[43]. Therefore, employing features of both physical and cognitive tasks may significantly improve the detection of cognitive impairment. In future work, we plan to incorporate features related to cognitive performance to improve the detection performance. To do so, we need to automate the cognitive feature extraction, such as by employing voice recognition, so that the system still can work automatically.

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