Identifying Central Nervous System Disorders from Daily Walking Activities

Gait abnormality is a main symptom of central nervous system (CNS) disorders which are a group of disorders including cerebrovascular disease (CVD), Parkinson's disease (PD), Alzheimer's disease (AD), and Huntington's disease (HD). Such CNS disorders are prevalent, devastating but poorly treated especially in the early stage. Daily monitoring and assessment may solve this problem, yet the related technique in this aspect still face big challenges. In this paper, we proposed a novel system for monitoring and assessment symptoms of CNS disorders with daily walking activities in a clinic and a workplace scenarios. We first introduced the method for extracting individual gait from daily walking activities, then we presented how we extracted features reflecting symptoms in CNS Disorders and, finally built a model with these features for identifying CNS disorders. In a study with 49 CNS disorders patients and 46 age-matched healthy people, we found that our approach achieved 83.31% average accuracy using 23-dimension gait features. This result demonstrate the feasibility of identifying CNS disorders via daily walking activities.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability

KEYWORDS

Gait; CNS disorders; daily monitoring; auxiliary analysis diagnosis

ACM Reference format:

1 INTRODUCTION

CNS disorders like Parkinson's disease (PD) and cerebrovascular disease (CVD) have severely affect patients' life quality for the symptom of freezing gait, tremor, rigidity and dysphagia. As a typical chronic disease of aging, PD has an increasing rate for the elderly population becoming larger in recent years. In 2015, PD affected 6.2 million people and resulted in about 117,400 deaths globally [1, 2]. Traditionally, PD and other CNS disorders have to be diagnosed via complex cognition and motor function tests and neurological assessment tools by physicians in hospital. Such diagnose procedures are tedious for both physicians and patients. However, CNS disorders are very likely to be mistreated as they are difficult to spot and costly especially in the early stage. Daily monitoring and assessment becomes a necessary method to assist the diagnosis and treatment of CNS disorders.

Previous studies shown that CNS disorders may cause motor function impairments, and these impairments often lead to symptoms of gait abnormality. As a result, researchers found that human gait have a strong relationship with CNS disorders [3] and, developed effective tools to monitor CNS disorders via gait motion [37]. In addition to the high monitoring sensitivity, the ubiquitous nature of walking activities make it possible to extracting gait abnormality from people's everyday life, and spot the symptoms of CNS disorders in early stage.

In this paper, we use Kinect to collect human's daily gait data —just walking a few meters naturally in front of Kinect sensor without any predetermined task. Then we translate the raw data into individual gait segmentations and extract 23-dimension motor features (like step width, step length and average speed, etc.) from them. And with the help of these task independent features, we built a classifier that can identify patients suffering CNS disorders from health participants. We conducted two studies to evaluate our approach. The first one evaluated the feasibility on extracting induvial gait in non-task scenarios, while the second one tested weather our method can identify CNS disorders quantitatively and accurately. In the second study, 96 subjects including 49 CNS disorders patients and 46 age-matched healthy people were recruited, and our approach showed an average accuracy of 83.31% (precision 85.14% and recall 87.50%) in identifying CNS disorders.

We summarize the major contributions of this work:

—We built a practical framework to collect data and extract gait abnormality features from daily walking activities in a non-task scenario.

—We built a model with 23-dimension motor features from individual gait data to identify CNS disorders and provided a pathological analysis on these features.

—We conducted empirical evaluation on the feasibility and generalizability of our approach to investigate whether it can be actually used in daily monitoring for CNS disorders.

2 RELATED WORK

CNS disorders can be clinically diagnosed with neurological assessment tools including exams, tests and special procedures such as the action research arm test (ARAT) [4], Wolf motor function test (WMFT) [5] and the clinical dementia rating (CDR) [6]. Wisconison Gait Scale (WGS) [7] and Gait Abnormality Rating Scale (GARS) [8] are two kinds of motor function evaluation scales that are widely used in clinical gait examination. WGS scores the examinee's ipsilateral standing phase, ipsilateral walking phase and ipsilateral heel strike subjectively. Many of its applications [9][10] have been proven to be credible in clinical diagnoses. GARS and its improved version call GARS-M have also been widely used in predicting falls for the elderly [11][12][13]. Tinetti Performance-Oriented Mobility Assessment (Tinetti POMA) [14] provides subjective assessments including aspects of hesitation starting, step height, step length, gait symmetry, and step continuity and, the scale for the assessment and rating of ataxia (SARA) [15] including gait assessment, posture assessment, language assessment, finger tracking test etc. gives an overall score about the patients' motor function to identify CNS disorders. However, these procedures are time-consuming for both doctors and patients and can only provide subjective assessment that usually varies among different experts.

With the development of information technology, it becomes possible to assess the symptoms of CNS disorders quantitatively. Researchers used image-based algorithms to process the MRI images for brain lesion detection [27] and tumor detection [28]. A multi-camera motion capture system was used to record the abnormal patterns of upper limb motion for children with cerebral palsy [29]. Ultrasound emitters were set up around a treadmill to record gait-related arm swing measurements for early PD diagnosis [30]. Accelerometer data was used to estimate the severity of symptoms and motor complications in patients with Parkinson's in clinic [18]. Other researches extracted measures related to tremor and spatial planning from handwriting to distinguish PD from healthy control (HC) [35] [36]. A GAITRite system is a tool to use pressure signal to measure multiple spatio-temporal components of gait, studies on this system found important measurements such as cadence, step length and velocity that can be useful for clinicians as indicators of disease progression [21] [22]. Although these methods generate consistent and accurate measures for objective diagnosis, many of them have to conduct by medical specialist with specialized medical facilities, the challenges of daily monitoring of CNS disorders remain.

Researches in Ubiquitous Computing and Human-Computer Interaction (HCI) communities have shown that human activities are affected by their motor and cognitive functions, which indicates the feasibility of assessing the functionality of the human body through such motion patterns [33] [34]. An increasing number of studies in these fields have developed techniques to assist CNS disorders monitoring and diagnosis. For example, studies indicated that eyewear technologies are acceptable [20] and can provide assistance to people with PD at home [19], they offered insights for the design of future self-monitoring and management applications on such technologies. Smartphone is one of most popular daily used wearable devices, and study was conducted to test the feasibility of detecting motor impairment in PD via implicitly sensing and analyzing users' everyday interactions with their smartphones [16]. As we mentioned, gait abnormality is one of the main symptoms related to CNS disorders, thus the full body gait analysis also attracted researchers' attention in ubiquitous computing and HCI communities. Motor sensors are also used to analyze the relationship of gait function and CNS disorders in step activity [23] [26], reduced walking [24] and instability [25]. Recently, with Microsoft Kinect device, researchers developed an accurate gait analysis system that is economical and non-intrusive [17] [37], and it is proven that this system can extract comprehensive gait information from all parts of the body. These kinds of approach are close to ours in this paper. However, they still rely on specialized walking tasks and need to be performed by

physicians during clinical visits. Since patients may not be aware of the symptoms when CNS disorders in the early stage, most of them may not go for a clinical visit in time.

3 METHODOLOGY

3.1 System Overview

To assess the targets' (i.e. one or more registered patients) motor functions in daily non-task scenarios, our system should have the following 3 key capabilities:

—Identify people in the video streaming, extract and map the skeletons in the video to the targets.

The system may run in any daily environment (e.g. workplace, home), thus there may be more than one person appear in the video, and they may be irrelevant to the assessment (e.g. the patient's colleagues or family members).

—Identify people's activities in the video streaming, extract the video segments belong to walking activities from the video.

For daily monitoring CNS disorders, the camera should run uninterruptedly in the field, thus the targets may perform various activities (e.g. sitting, standing) in front of the camera other than just walking.

—Extract pathological features from targets' walk activity and use them to identify CNS disorders quantitatively.

To implement the system, we built a processing workflow in our system to collect, process and analyze gait data in this study. Firstly, face recognition technology was used to the people in the video. Secondly, we identified gait segments in the video and extracted 23 kinematic features in these segments to describe people's state of motion. Finally, we collect the gait data both CNS disorders patients and the control group using our system to build an auxiliary diagnosis model. The overall processing workflow of the system includes video recording, face-skeleton matching and motor function assessment (Fig. 1).

—Video Recording: A depth camera which we use to record people walking, was placed in a passage of office, hospital or even home. Both color stream and depth stream were collected for hours. After the raw data has been captured, data processing techniques were used to pre-process them.

—Face Recognition: To identify different people passing through the passage, we take a photo for every target person who we mean to monitor and assess the gait function. Then we use CNN to track and recognize the faces in the color stream.

—Skeleton Extraction: Kinect SDK helps us to get at most 6 people's skeleton data at the same time in the depth stream.

—Face-Skeleton Matching: After the face recognition we can get the detected faces locations and their ID. We transform the coordinates of color frame to 3D camera space and then find the matched skeleton in this frame.

—Motor Function Assessment: We extract 23-dimention features related to the gait functions from the face-matched skeletons. Feature analysis techniques and machine learning algorithms were used to help doctor to assess the motor functions of targets.

In the following chapters, we will describe the key techniques in the workflow.

Fig. 1. The processing workflow of our system.

3.2 Video Recording

We use Kinect 2.0 camera which provide both color frame (1920 * 1080) and depth frame (512 * 424) in 30 fps to record the video. We save color stream and depth stream separately preparing for the following face recognition and skeleton extraction steps. The two color stream and depth stream were encoded with x264 H.264 and Kinect 2.0 default format respectively to reduce the hard disk consumption.

3.3 Face Recognition and Skeleton Extraction

As it is shown in Fig. 2, a face-skeleton matching method was implemented. We use Davis King's Dlib model to recognize face in our color stream video [31]. The model is a network with 29 convolution layers, which can correctly predicts wether the given two face images are of the same person 99.38% of the time [32].

To initial our system, we take a photo of every target's face and get its face encodings with the above model. We detect faces in every frame of separated color video and then compare these detected faces' encodings with the initial ones. If matched, we store the face location coordinates, the current frame number and its target ID, preparing for the following face-skeleton matching.

The skeleton data were extracted using Kinect 2.0 built-in API.

3.4 Face-Skeleton Matching

Kinect can provide us skeleton data belong to 6 different people at most in the rate of 30 fps. This skeleton data is the foundation of gait feature calculation. To get the specific person's gait feature, we need to know which skeleton in the depth stream belong to the target person. When processing the skeleton data frame by frame, we map the stored face recognition data to the skeleton frame. Firstly, for every frame which has the detected faces information, we transform the 2D face location coordinates into the 3D camera space point's coordinates by the Kinect CoordinateMapper. Secondly, we calculate the Euclidean Distance between the face location and every skeleton's head joint. The nearest one will be marked with the face ID. Finally, to prevent the error face recognition or mismatching of face and skeleton, we formulate the matched ID of every frame as a time sequence and implement a majority vote algorithm on it. As shown in ALGORITHM 1, we finally get a face ID which occurred most frequently in the time sequence as the matched ID of this skeleton.

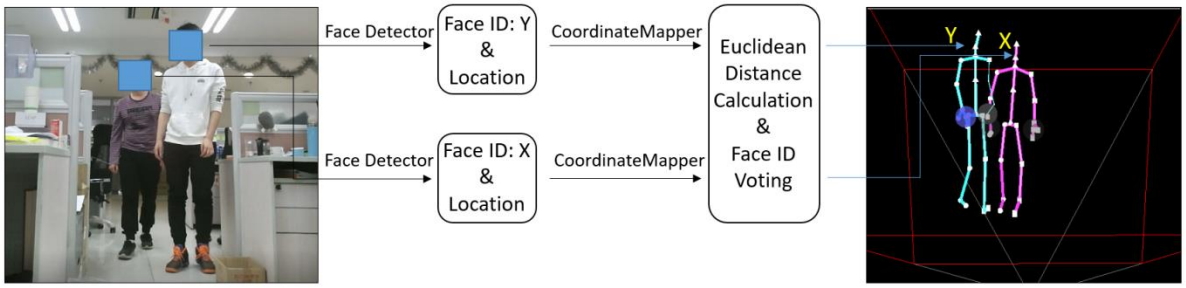

Fig. 2.The workflow of face-skeleton matching method.

ALGORITHM 1: Majority Vote Algorithm

```
current_ID ← null
count ← 0
final_matched_ID ← null
for each ID in ID_sequence, do
        if count <= 0 then
                count ←1
                current_ID ←ID
```

```
        else if current == ID then
                count ←count + 1
        else
                count ←count - 1
                if count <= 0 then
                        count ←1
                        current_ID ←ID
                end
        end
end
if count >= threthold then
        final_matched_ID ←current_ID
end
return final_matched_ID
```

3.5 Feature Extraction

For both purposes of gait segmentation and CNS disorders identification, we extract 23 gait features to characterize targets' walking state. These features are generated using statistical methods sum, maximum, minimum, mean and variance to get overall properties of gait step velocity, step high etc., see Table 1.

Table 1. All the 23 features and the abbreviations used in the motor function assessment

Feature	Abbreviation	Feature	Abbreviation
walking velocity	WV	right-step height mean	RHM
right-step velocity mean	RVM	right-step height variance	RHV
right-step velocity variance	RVV	left-step height mean	LHM
left-step velocity mean	LVM	left-step height variance	LHV
left-step velocity variance	LVV	coordination of step height	CSH
cycle velocity mean	CVM	step width mean	SWM
cycle velocity variance	CVV	step width variance	SWV
right-step length mean	RLM	pace distance mean	PDM
right-step length variance	RLV	pace distance variance	PDV
left-step length mean	LLM	Z-angle mean	ZM
left-step length variance	LLV	Z-angle variance	ZV
coordination of step length	CSL	/	/

—Velocity related features:

WV, RVM, LVM and CVM are all velocity related features. According to the neurologists' experience, walking velocity of CNS disorders patients is always lower than the age-matched healthy people. We calculate these features by finding the coordinates and time points when target's foot joints come into contact with ground plane.

—Stride related features:

RLM, LLM, RHM, LHM and PDM are all stride related features. As split step is a typical kind of gait abnormality, we expect to find the quantifiable data to describe this symptom by these stride based features. We calculate these features by monitoring the coordinates of people's foot joint in skeleton stream.

—Balance related features:

SWM and ZM are balance related features. We extract these two features to describe the ability of patient's posture controlling. SW is the average value of the tangential distance between a target person's left foot and right foot while he is walking. And ZM is the average value of angle between a target person's head-waist line and ground plane.

—Variance related features:

RVV, LVV, CVV, RLV, LLV, RHV, LHV, SWV, PDV and ZV are all variance related features. Rest tremor, action tremor and intention tremor are common symptoms of CNS disorders. We expect these variance based features describing the tremor degree of patients.

—Coordination related features:

CSL and CSH are coordination related features. We extract the features to describe the coordination of people's bilateral limbs as the motor function damage degree of bilateral limbs is always different. Many patients tend to lose his motor function in one side of limb.

3.6 Gait Segmentation

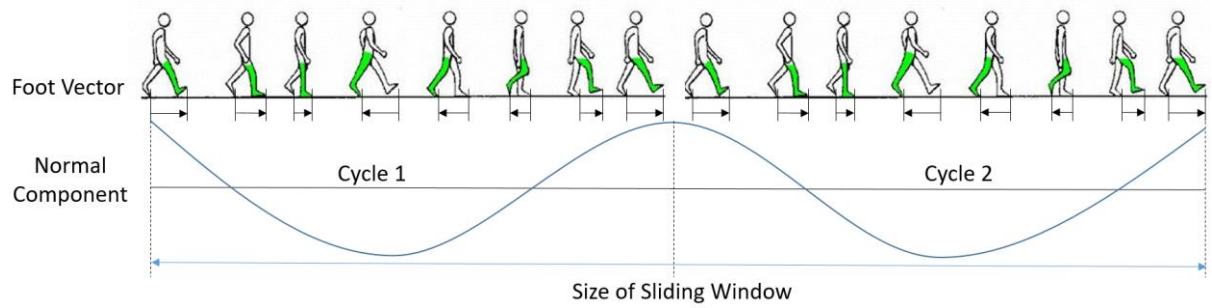

Fig. 3. Gait cycle segmentation and sliding time window.

We implement a classification approach with 4 steps to identify whether the targets' is walking or performing other activities in the video. Firstly, we calculate the Foot Vector between right toe and left toe. Secondly, we calculate the normal component of the Foot Vector and find its maximum and minimum; the period between the maximum and minimum defined a gait cycle. Thirdly, we define the time of 2 cycles as the size of sliding time window; while the time window sliding on the skeleton frames, we calculate kinematic and statistical features. Finally, we train a walking activity classifier to identify whether the target person is walking in the current time window. The walking activity classifier is trained with the above 23 features reflecting the motion state of targets. Fig. 3 shows the gait cycle segmentation and sliding window size.

3.7 Motor Function Assessment

After feature extraction and gait segmentation, we used the segmented gait clips to access the symptoms of CNS disorders. We analyze the 23 features extracted from these clips to evaluate their correlation with CNS disorders.

Significance test was used between CNS disorders group and control group for every feature above. We calculate the P-value to show the difference between patients and age-matched healthy people, which can help us to know the motor function damage details caused by CNS disorders.

We then build a prediction model to identify patients suffered CNS disorders from HC group. To get a better classification model, we use Linear Discriminant Analysis (LDA) to make dimension reduced. Then we

implement 5 machine learning algorithms including support vector machine (SVM), logistic regression (LR), gradient boosting decision tree (GBDT), random forest (RF) and k-nearest neighbor (KNN) to build the classification model.

Finally, data visualization methods were used to make an assessment report for neurological physicians and patients. Time-domain plot, scatter plot, heat maps and histogram were used to in the assessment result to make a clear view.

4 Experiment

The gait segmentation phase of our system was tested in the workplace of the research team, and the assessment phase was evaluated in a clinic. We did this because we did not get the permission to put our system in a ward of CNS disorders patients to collect real gait data of daily monitoring for ethical and privacy issues. We are still applying for ethical review with our cooperative hospital. Fortunately, we got the permission to put our system in a real neurology clinic to collected patients' gait data under supervised.

4.1 Daily Monitoring in Workplace

A Kinect camera was settled at a passageway in an office, stimulating the environments that the patients may live in. There are 8 people work here every day and we choose 5 as our monitoring targets. We believe it is easy to find a passageway similar to the one showed in Fig. 4 in most companies and offices.

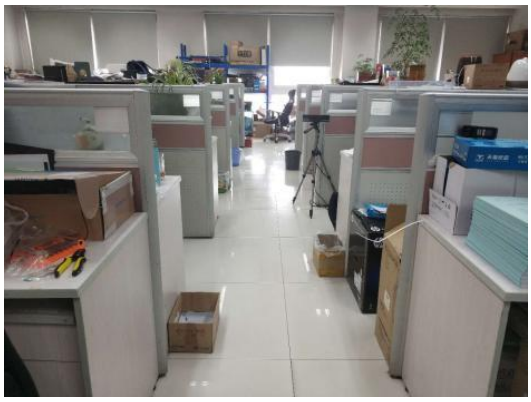

Fig. 4. Experiment environment in an office.

Before video recording, we take a photo of each target person's face as a baseline. We put these 5 photos into our face recognition model to get their face encodings. Then we record the video from 10:00 p.m. to 10:00 p.m. the next day for 24 hours. No matter when people appeared in the video and their faces were detected, we will calculate their face encodings and try to compare them with the baseline face encodings to find a most matched one. After finding a matching target, we store his face location and ID for further face-skeleton matching. However, people beyond our targets may also appear in the video and our face detector can detect their faces, too. We calculate these face encodings and their mismatching degree would be higher than a default value (0.6 in our experiment). Then we marked their ID as *Unknown* and also pass these face locations to find their matching skeleton to help us exclude these unnecessary skeleton data. A few matching errors are tolerable with the help of majority voting in ALGORITHM 1.

After face-skeleton matching, we calculate all the 23 features showed in Table 1. for every sliding window. A logistic regression classifier trained by 40 walking-only video data and 40 not walking video data (including standing, sitting down and standing up or people chatting together, which appeared frequently in the office) and

20 mixed video. We labeled the 40 walking-only video as positive data and the other 40 as negative data. The 20 mixed video were labeled randomly as weak supervised data. The classification result is shown in Table 2.

Table 2. Walking or not classification result with logistic regression classifier

Accuracy	Precision	Recall	F1
91.00%	0.9053	0.9600	0.8800

In every sliding window, we calculate the 23 features and put them in our classifier to get the likelihood probability of walking and the predict label. If the label of the current window is positive, we would store the features in a buffer, if not, we would abandon the data of this window. Finally, we use the average value as the final features of the target person. Fig. 5 shows the partial results of our office 24h monitoring.

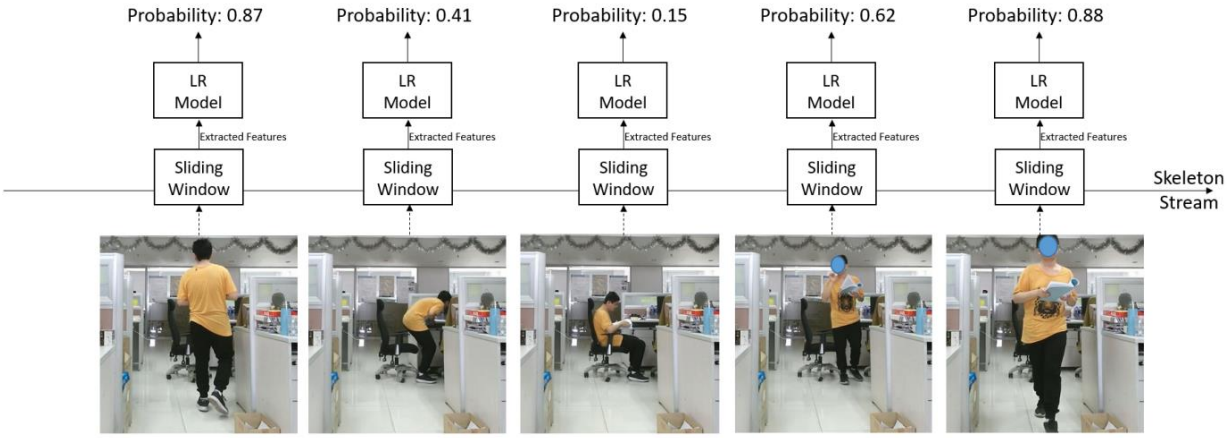

Fig. 5. Partial results of our office 24h monitoring on identifying whether people is walking.

4.2 Assessment CNS Disorders in Clinic

Fig. 6 shows that the doctor was diagnosing a patient using our system. Different from monitoring in the office, doctors will indicate patients to walk about 3 meters to and fro in front of Kinect camera. In this situation, patients mainly conducted make three kinds of activities under the supervise of a doctor. These activities include walking, hand movements in sitting pose and hand movements in standing pose. We used the same gait segmentation method to extract the induvial skeleton and gait features of patients from these recording automatically. We observed a good enough matches between the outputs of our method and manually labeling results.

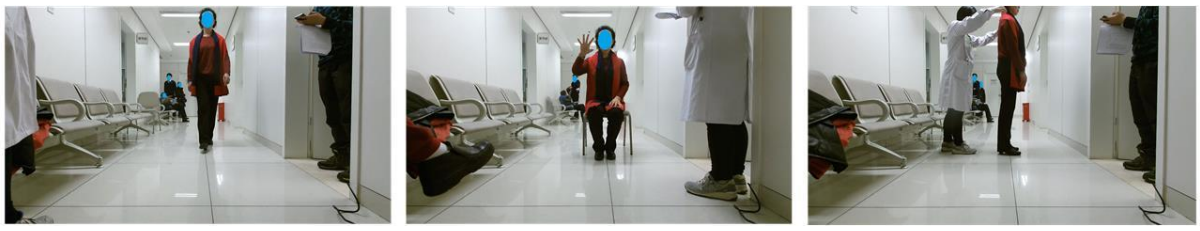

Fig. 6. Doctor is diagnosing a patient with our system.

We collected 49 CNS disorders' gait data in a clinic in our cooperative hospital. In addition, we collected the data of HC group include 303 healthy people in a community health survey using our system, see Fig. 7.

Fig. 7. Community Health Survey.

Based on the collected data, we build a prediction model to identify CNS disorders from the healthy people, to give neurologists an overall diagnosing suggestion. 49 CNS disorders' gait data from the clinic were marked positive label and 46 age-matched chosen people's gait data from the survey were marked as negative. 5 supervised learning algorithms were implemented and their classification results were showed in Table 3.

Table 3. Classification result of CNS disorders vs. healthy people.

Classifier	Accuracy	Precision	Recall	F1	AUC
SVM	**83.31%**	0.8362	0.8750	0.8419	0.8885
GBDT	82.08%	0.8300	0.8350	0.8294	0.8970
KNN	83.19%	0.8243	**0.8950**	**0.8482**	**0.9184**
RF	82.08%	0.8250	0.7950	0.7602	0.8630
LR	81.19%	**0.8514**	0.7950	0.8129	0.9180

All of our five algorithms were validated through 10-fold cross-validation, and average classification accuracy, precision, recall, F1-measure and area under ROC curve (AUC) of the CNS disorders patients of the final classifiers were provided in table 3. From the table, we can see that the best accuracy was achieved by SVM (with RBF kernel) classifier with 83.31%. The best precision was achieved by LR model with 0.8514 and the best Recall (0.8950), F1-measure (0.8482) and AUC (0.9184) were achieved by KNN model. All the classification results have proved that our approach can identify CNS disorders patients from healthy participants in a significant measure.

In the following sections, we provide statistical analysis and visualization of the collected data to further evaluate the reliability of our approach and, give an insight to clinic diagnosis with gait data.

We use T-test to indicate the differences between CNS group and HC group in each feature, all the 23 features p-value in the T-test were showed in Table 4.

Table 4. Analysis of the significance of 68 features

Feature	Control Group	CNS disorders	P -value
WV	1.094 ± 0.731	0.851 ± 0.501	0.0135*
RVM	1.473 ± 0.581	1.333 ± 0.663	0.0165*
RVV	0.067 ± 0.188	0.050 ± 0.083	0.1774
LVM	1.389 ± 0.650	1.326 ± 0.730	0.9178
LVV	0.041 ± 0.112	0.033 ± 0.054	0.3381
CVM	1.207 ± 0.327	1.080 ± 0.431	0.0140*
CVV	0.007 ± 0.022	0.013 ± 0.025	0.2742
RLM	0.424 ± 0.119	0.377 ± 0.139	0.0022*
RLV	0.002 ± 0.003	0.002 ± 0.003	0.8783
LLM	0.418 ± 0.124	0.372 ± 0.147	0.0021*
LLV	0.002 ± 0.004	0.002 ± 0.003	0.8265
CSL	0.058 ± 0.057	0.035 ± 0.028	0.0127*
RHM	0.455 ± 0.060	0.424 ± 0.110	0.0023*
RHV	0.004 ± 0.009	0.009 ± 0.013	0.0014*
LHM	0.461 ± 0.055	0.420 ± 0.105	<0.0001*
LHV	0.003 ± 0.008	0.009 ± 0.014	<0.0001*
CSH	0.028 ± 0.057	0.059 ± 0.080	0.0001*
SWM	0.080 ± 0.047	0.120 ± 0.059	<0.0001*
SWV	0.004 ± 0.004	0.004 ± 0.004	0.8474
PDM	0.443 ± 0.145	0.409 ± 0.152	0.0360*
PDV	0.005 ± 0.008	0.004 ± 0.007	0.3045
ZM	59.58 ± 2.344	59.21 ± 1.880	0.8226
ZV	6.317 ± 7.922	6.768 ± 7.554	0.7204

From the above table, we find that WV, RVM, CVM, RLM, LLM, RHM, RHV, LHM, LHV, CSH, SWM, PDM features are all have significant difference between CNS disorders group and the control group. Walking velocity and other velocity related features of CNS disorders patients is obviously lower than the control group, which conform to our subjective experience. Step length and step height related features are also lower than the healthy people, which means CNS disorders make significant motor function damages to people's lower limb. The CSL and CSH features showed that coordination of patients' lower limb also occurs an exception. Step width of patients is significantly higher than the control group is a new finding.

Feature distribution plots give another view to understand the features' discrimination ability and the prediction model. As Fig. 8 shows, most of features on distance mean value and velocity mean value appears obviously different distributions, which reflects the symptoms of gait freezing and bradykinesia. However, distributions of majority of features related to variance showed no significant difference between CNS disorders group and the control group. We set these variance-based features hoping to reflect the symptoms of static tremor and kinetic tremor, while the final result is out of our expectation. However, LHV and RHV is an exception. We speculate that features on step height can reflect the ability of a patient holding foot away from the ground. And holding action can stimulate the symptoms of tremor so that only the variance on step height shows significant difference

between CNS disorders patients and healthy people. The distribution of step width also proves the findings we get from the above significance test.

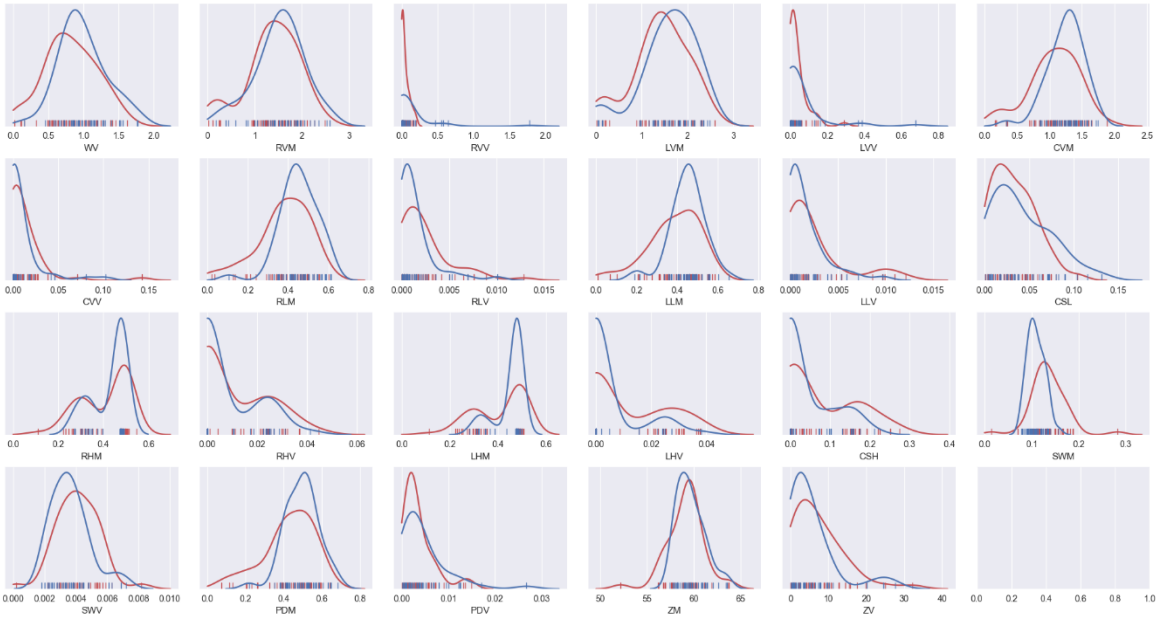

Fig. 8. The distribution of all the 23 features (Red curve: CNS disorders group; Blue curve: control group).

During the data collection in clinic, we found that many CNS disorders patients tend to loss their motor functions on one side of the body. To find whether CNS disorders is more prone to damage motor functions of the left lower limb or the right, we make a joint visualization of LLM and RLM in Fig. 9. From this joint distribution plot, we find no significant bias appeared on the motor function damage of left or right lower limb in both CNS disorders group and the control group. All the hex blocks distribute around the diagonal nearly symmetrically. Besides, the distribution area in the left plot is much larger than the right and the whole area tends to be in the lower left, which indicates that CNS disorders patients' motor functions decline a lot. Pearson's coefficient in the left plot is larger than the right, which coincides with the P-value result of CSL feature. Larger step length of the control group cause larger CSL while CNS disorders patients' symptom of random little step tend to smaller CSL.

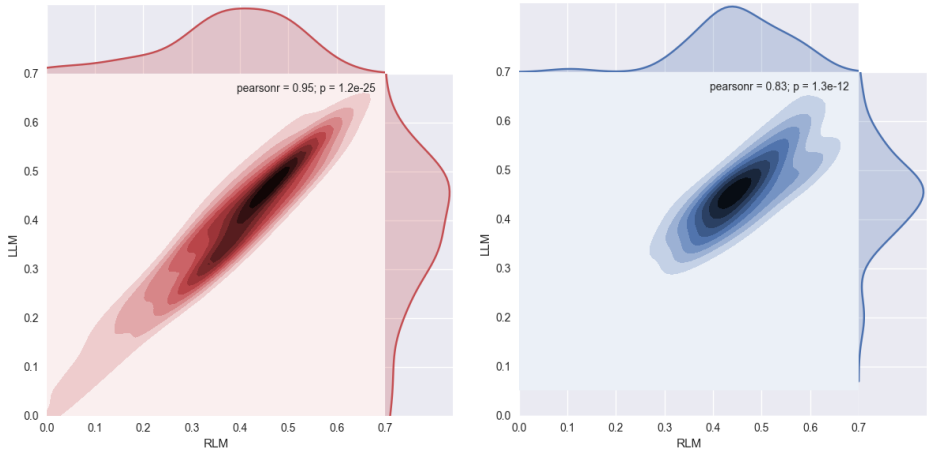

Fig. 9. The heat map joint distribution of LLM and RLM (Left: CNS disorders group; Right: control group).

Fig. 10 gives the heat map of LHM and RHM. Larger distribution area than the control group proves that CNS disorders patients are losing the ability of lifting and holding lower limb when walking.

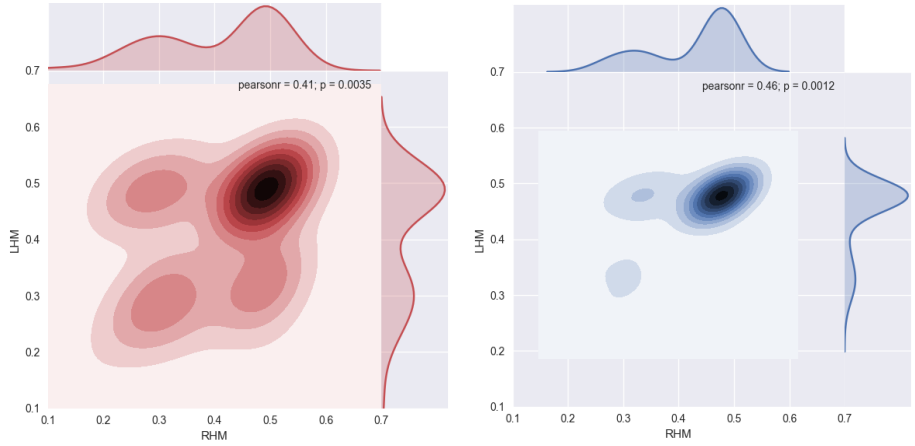

Fig. 10. The heat map of joint distribution on LHM and RHM (Left: CNS disorders group; Right: control group).

5 CONCLUSIONS

CNS disorders may cause motor function impairments resulting significant symptoms of gait abnormality. With the modern technologies of ubiquitous computing and HCI, it is possible to capture a full range of information from people's daily walking activities. Therefore, such assessment for CNS disorders could be incorporated into daily monitoring and medical decision support systems. All walking activities can be easily captured by a depth camera, either during a clinic visits or at patients' workplaces. From the studies in this paper, we envision that the diagnosis and assessment of CNS disorders could be conducted anywhere and anytime in the near feature.

To investigate whether and how we can identify CNS disorders with daily walking activities, we conducted an exploration on technique framework, crucial algorithms, key features and classification models in such scenarios. In this study, we collected data from 95 participants, analyzed 23 features from gait, built 5 classification models

to identify CNS disorders. The best classification accuracy, precision, recall, F1-measure and AUC are 83.31%, 0.8514, 0.8950, 0.8482 and 0.9184. All of our classification models are general machine learning algorithms, which indicate that our approach has a good generalization ability. In addition, statistical analysis and data visualization were used to help neurological physicians investigate the relationship between motor function damages and CNS disorders in this study.

In the feature, we are interested in extending our research in two aspects. First, we should enlarge our dataset, collect more subjects from different kinds of CNS disorders, reducing the chance of overfitting and enhancing the robustness of our models. Second, we should conduct field study on different applications running in different scenarios, such as wards and home, thus we can evaluate our approach in real unsupervised situations.

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A HEADINGS IN APPENDICES

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