Wearable Computing of Freezing of Gait in Parkinson's Disease: A Survey

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Abstract

Freezing of Gait (FoG) is defined as a sudden and short event in which a patient loses the ability to step forward. Advanced Parkinson's Disease (PD) patients frequently experience these events. When FoG occurs, falling is possible and this has a severe influence on patients' quality of lives. Recently, the research on detecting and predicting FoG and falls in PD has increased rapidly. However, there has not been a recent systematic survey in this area to conclude the efficacy of wearable devices in both detection and prediction in different environments (clinical, laboratory, home). Thus, this survey summarizes the previous research on FoG computing in sensor selection, feature extraction, algorithms and performance, which provides sufficient background knowledge on the state-of-the-art research. In this paper, we discuss a series of FoG challenges and integral future research trends, which will allow for the advancement of further research.

Keywords: Parkinson's Disease (PD); Freezing of Gait (FoG); FoG Computing; Wearable Computing; Detection; Prediction

1. Introduction

Parkinson's Disease (PD) is a progressive neurodegenerative disease which impacts millions of patients [1]. For many PD patients, FoG and its associated fall risk are the most concerning disabling problems [2]. Pharmacological interventions are currently limited [3]. Some wearable devices that provide interventions, such as rhythmical cueing and step-synchronized vibratory cueing, have satisfactory performance [4] [5]. To treat the FoG efficiently, FoG detection and FoG prediction are emerging as a subject of research.

In this paper, we summarize the previous work of FoG computing in four aspects: sensor selection, feature extraction, algorithms, and performance. In the sensor selection section, we go through and introduce the off-the-shelf sensors (e.g. pressure sensors, motion sensors, etc.), and clinical sensors (e.g. EEG, ECG, EMG, etc.) in FoG computing. And we summarize this in Table 2. In the feature extraction section, we detail the time-domain and frequency-domain features employed in FoG computing. In the algorithm section, we describe all the algorithms that have been utilized in FoG computing and separate them into two main categories: threshold-based algorithms and learning-based algorithms. Next, we introduce the algorithms and how they are applied in FoG detection and prediction. Lastly, in the performance section, we show the performance metrics that are widely used in the evaluation of FoG computing and other wearable computing. We summarize the performance of previous research on FoG detection and prediction (see Table 3 and Table 4).

Some surveys have summarized previous work on both PD and FoG (Section 2.3). However, there is not a survey so far that summarizes both FoG detection and FoG prediction with the details of different approaches. We begin with the sensor selection to choose the hardware device, and then we go through feature extraction and algorithms to select the classifier. Finally, we compare all the FoG detection and FoG prediction work to present the state-of-the-art performance based on different sensors and classifiers.

Figure 1 shows the overview of this survey. In Section 2, we introduce the background knowledge of PD and FoG, FoG intervention with wearable devices, and related surveys in PD and FoG. In Section 3, we present the

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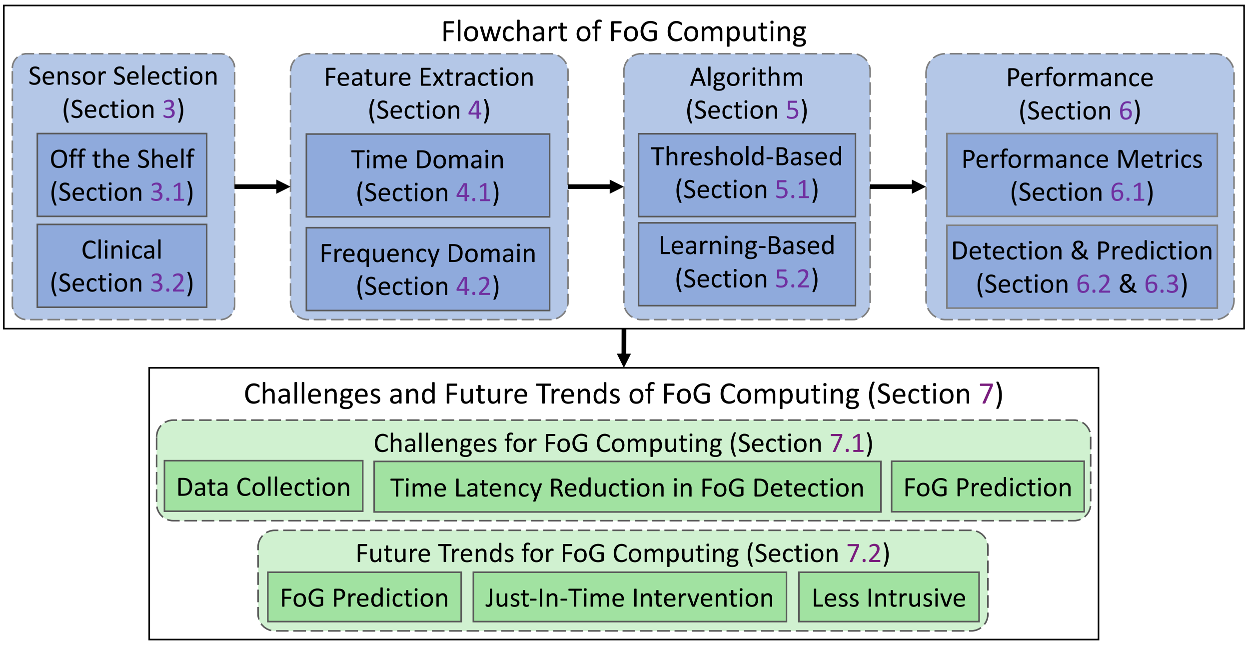

Figure 1: Flowchart of FoG computing

sensor selection including the different introduction of widely used off-the-shelf sensors and clinical sensors in FoG computing. Characteristic features extracted from both time-domain and frequency-domain are shown in section 4. Next, we include threshold-based algorithms and learning-based algorithms that have been employed in FoG computing in Section 5. Then, the performance metrics and the performance for FoG detection and prediction are presented in Section 6. Last, we summarize the insights to propose the challenges and future trends for FoG computing for future researchers to work on. In summary, the contributions are as follows:

1. We summarize the background knowledge, intervention, and related reviews of FoG and PD, which may inspire future researchers to easily get involved in this research field.
2. We completely summarize, introduce and discuss previous research on sensor selection, feature extraction, algorithm, and performance in FoG computing.
3. Based on the insights of the survey, we identify a series of challenges and future research trends, which will improve future research in FoG detection and prediction.

2. Background & Related Work

In this section, we present the background knowledge of PD and FoG, the intervention of FoG, and related survey for PD and FoG. We briefly introduce what PD and FoG are and how people are struggling with them. Then, we present the intervention of FoG and explain how FoG can be mitigated both in clinical and home environment. Next, we go through the related works on the background information about PD and FoG, the intervention for PD and FoG, FoG wearable computing surveys, etc.. Lastly, we discuss the differences and advantages of this survey compared with others.

2.1. Background of PD and FoG

PD is a disease which is continuous degenerative of the central nervous system with more than 10 million patients worldwide and is expected to continue increasing in number [6]. PD is identified by four main motor symptoms: postural instability, rigidity, bradykinesia, and tremor. Also, non-motor impairments like executive dysfunctions, memory decline, and smelling ability reduction may occur concurrently [7] [1] [8]. FoG difficulties and fall risk are some of the most concerned disabling problems in many PD patients. According to a survey of more than 6,000 PD patients, 47% of them suffered from regular occurrences of FoG, and nearly 60% of them suffered from FoG every day [9].

FoG often occurs when a patient is navigating narrow spaces, turning while performing other actions, and moves from standing to walking [2] [10] [11] [12] [13]. With the deterioration of the disease, incidences of FoG episodes increase, and the effectiveness of medications decrease. This amplifies the burden of the symptoms of the disease [12] [14] [15]. The FoG risks include falls [16], loss of mobility and independence and even death [17]. These risks can cause nervousness and anxiety and a decrease in a patient's quality of life.

2.2. Intervention of FoG

The management of FoG often includes two types of interventions: pharmacological treatments and deep brain stimulation (DSB). Typically, PD patients can take manipulated dopaminergic medicine to maintain the normal state. However, pharmaceutical are not very effective when treating FoG. A dopaminergic medicine L-dopa will lose effectiveness as the disease becomes severe and it can also increase the severity of FoG [3]. Methylphenidate (MPH), which has been commonly employed in attention disorder treatment, is another pharmacological treatment [18]. However, [19] mentioned that MPH had shown unclear findings with both positive results and negative results in different studies. Also, [19] concludes that DSB is expensive and invasive compared with pharmacological treatment, and the results are also not so clear.

Since clinical interventions are expensive and ineffective, researchers have proposed some other treatments for FoG, such as external rhythmical cueing and step-synchronized vibratory cueing. Even though they can not fundamentally treat the FoG or PD, they can help patients to relieve the symptoms of FoG. To help patient exit from an FoG event and continue walking, researchers propose rhythmical cueing such as a continuous periodic ticking sound can synchronize the patient gait [4] [5] [20], [21] [22] [23]. On body sensors and feedback devices can detect FoG and generate a rhythmical cue to mitigate the symptoms and risks associated with FoG. Another method is step-synchronized vibratory cueing, which is still in the early stage of research. [24] first employed the pilot study to explore how augmented sensory feedback improves Parkinson's gait stability in a short period. [25] can improve gait metrics in a clinical setting with their step-synchronized vibratory cueing wearable device. These two approaches are unobtrusive and can be applied in any environment, which can be commercialized in the future.

Table 1: Summary of Related Surveys and Reviews on PD and FoG

Reference	Scope	Topic Focus
[26]	PD Background	Background Knowledge and latest progress about PD
[27]	PD Intervention	Levodopa dose equivalency reporting in PD
[28]	PD Depression	Prevalence studies of depression in PD
[29]	PD and Technology	The challenges and opportunities of technology in PD
[30]	FoG Background	Cross-Sectional Study of FoG and its associations and clinical motor stages
[31]	FoG Background	Background knowledge and the-state-of-art progress of FoG
[16]	FoG and Falls Intervention	Clinical presentation on FoG and Falls
[32]	FoG Intervention	Clinical and wearable intervention of Gait
[22]	FoG Intervention	Sensor-based Cueing for the Intervention of Gait
[33]	Gait Analysis with Wearable Sensors	Review of gait analysis methods and feature extraction
[34]	FoG Detection with Wearable Device	Clinical and wearable device comparison on FoG detection
[35]	FoG Detection with Wearable Device	Summary of FoG detection works

2.3. Related Work

Researchers have published some surveys on PD and FoG, including PD background knowledge, intervention, technology, etc., and FoG background knowledge, intervention, wearable computing, etc.. Table 1 presents related surveys and reviews in these fields. [26] [28] are some representative reviews on PD background knowledge and latest progress about PD. [27] introduces the levodopa dose equivalency and intervention of PD, while [29] shows the challenges and opportunities of technology in PD. In FoG fields, [30] [31] introduce the FoG background knowledge and the-state-of-art progress of FoG. Next, [16] [32] [22] present the Intervention of FoG in both clinical and wearable domains. [33] gives a review of gait analysis methods and feature extraction techniques. Also, [34] shows the comparison between clinical and wearable devices on FoG detection. Last, [35] summarizes the FoG detection works with some large tables mainly on the sample, type of sensors, sensor locations, procedures, and main contributions of each paper.

Unlike the previous surveys and reviews on PD and FoG, our scope is focusing on FoG computing which contains the application of both FoG detection and prediction. We first briefly introduce the background knowledge and intervention methods of FoG. Then, we mainly focus on presenting the sensor selection, feature extraction, algorithms, and performance of FoG detection and prediction, which comprehensively introduces the FoG computing process and methods. We present this survey to help the researchers who are concentrating on FoG computing and state-of-art works in the FoG computing area.

Table 2: Sensor Selection for FoG Detection and Prediction

Type	Sensors	References
Pressure Sensors	Insole Sensor	[36]
	Pressure Platform	[37], [38]
Motion Sensors	Accelerometers	[39], [40], [41], [42],[43],[44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61],[62], [63]
	Accelerometers + Gyroscopes	[64], [65], [66], [67], [68]
	Accelerometers + Gyroscopes + Magnetometers	[69], [57]
	Accelerometers + Telemeter + Goniometer	[70]
	Gyroscopes	[71]
Clinical Sensors	EEG	[72]
	fNIRs	[73]
	ECG+SC	[74]
Other Sensors	EMG + Accelerometers	[75]
	EMG + Camera	[76]
	Depth Camera + Accelerometer	[77]
	Camera + Goniometer	[78]
	ECG+ Insole + Accelerometer	[79]

3. Sensor Selection

Sensing FoG events is one of the essential and fundamental processes of FoG detection and prediction. Since different types of sensors generally determine feature extraction and algorithm selection, it is necessary that we present sensor selection in this section. Based on different applications and principles, we have multiple choices in sensor selection. Typically, we classify the sensors as off-the-shelf sensors or clinical sensors. Off-the-shelf sensors are ready to purchase and simple to implement in a home environment. For clinical sensors, even though it is obtrusive and limited in a clinical environment, it still can provide valuable signals for FoG prediction and potentially contribute to the intervention of FoG and PD where off-the-shelf sensors are ineffectual.

Initially, some researchers selected pressure sensors placed in the insoles of shoes to detect FoG. Following that, as motion sensors became increasingly popular in wearable computing, researchers selected them to sense FoG events. This allowed for more robust and precise data with a simple and efficient implementation. Then, cameras and other video systems were added to the data collection process to increase the accuracy of the motion sensors. Later, however, researchers found that using only the motion sensors with flexible devices can still reach a high accuracy. Now, motion sensors are the most popular part of wearable device on FoG detection.

Motion sensors have been widely employed to detect FoG since FoG has apparent motion features when the event happens. However, before FoG occurs, there are not obvious motion features. This creates difficulty for prediction of

FoG with motion sensors. Even though slight signal patterns may occur, it is not enough to lead to prediction. Therefore, researchers divert their attention to mental conditions, which may be essential in the treatment of FoG.[14]. Under this hypothesis, the physiological data such as Electroencephalogram (EEG), Electrocardiography (ECG), Heart Rate (HR), Skin Conductance (SC) are introduced to capture specific features before FoG. Even though most of the physiological data needs to be collected from obtrusive clinical sensors, some data, like HR, can be acquired by a wearable device such as a smartwatch or a smart wristband. Therefore, physiological data also has the potential to predict the FoG episodes unobtrusively. Table 2 show previous work with different sensors. Next, we introduce the sensor selection in more details.

Figure 2: **UG Sensor: A combination of accelerometer, gyroscope, magnetometer**

3.1. *Off-The-Shelf Sensors*

Wearable computing devices are unobtrusive, portable, reproducible, and inexpensive. Therefore, off-the-shelf sensors, such as motion sensors, cameras, and insole pressure sensors are used to monitor FoG events. We detail these sensors and how they are employed in the FoG computing in the following paragraphs.

Since FoG is related to motor impairment, most previous research selected wearable motion sensors to detect abnormal gait behaviors. Motion sensors such as accelerometers, gyroscopes, and magnetometers are chosen most frequently to recognize FoG due to their unobtrusive, portable, low power consumption characteristics. Figure 2 shows UG sensor [80], a commercial hardware embedded with a combination of accelerometer, gyroscope, magnetometer, which is simple but effective. Among the previous work with motion sensors, there are three sensor choices. First, researchers solely worked with accelerometers. Second, researchers combined the accelerometer and gyroscope. Third, researchers exploited all three sensors: accelerometer, gyroscope, and magnetometer. Also, telemeter and goniometer have been exploited in preceding work. Next, we will present these cases one by one in the following paragraphs.

Initially, researchers attempted to use the insole pressure sensors to detect FoG events. The pressure sensors are embedded into the shoes to sense the step frequency. If the step frequency exceeded a threshold, they classified an FoG event. This threshold based classifier had a high rate of misclassification. Later, pressure sensors were replaced by motion sensors.

Microelectromechanical systems (MEMS) accelerometers are electromechanical devices that can measure static and dynamic acceleration forces caused by movement and vibration. For FoG detection, Han et al. [39] first utilized two MEMS accelerometers around the ankles to extract FoG features from the gait episodes. After they applied Fast Fourier transform (FFT) to the signals, they observed that a normal gait has a primary frequency of near 2Hz while FoG is near 6-8Hz. This proves that MEMS accelerometers can efficiently contribute to the classification between normal gait and FoG episodes.

Gyroscopes and magnetometers are two common motion sensors that can sense the variation of orientation and direction. Since the specific causes of FoG are unknown, to enhance the precision of applying the shallow learning algorithms to FoG detection, more data and features of FoG are needed. Therefore, some research like Tripoliti et al.[64], combine accelerometers with gyroscopes, while Mazilu et al. [69] combines accelerometers with gyroscopes and magnetometers to collect more features for the ML algorithms.

Recently Ali Saad et al.[78] employed telemeters and goniometers with accelerometers to detect FoG events. By sensing the voltage variation, telemeters can measure the distance variation between two devices while goniometer can measure the angle variation of joints. These devices are small, portable and energy efficient. To enhance the precision, telemeters measure the variation of the inter-foot distance during walking to detect each step, and they exploit goniometers to measure the angle of the knee.

3.2. Clinical Sensors

Motion sensors are effective on detecting FoG events, while they do not work well on predicting FoG episodes. Since FoG is caused by PD, traditional clinical sensors like EEG, ECG, EMG, fNIRS have been employed to help detect the FoG events. FoG events are commonly caused by reactions such as agitation, anxiety, and tightness in the patient. Clinical sensors can help to provide insight into these reactions. Even though clinical sensors sacrifice the convenience and low power consumption they produce less noise and potentially can perform better on FoG prediction.

Electroencephalography (EEG) monitors the electrical activity of the brain. It measures voltage fluctuations caused by ion currents in the brain neurons[66]. Typically, doctors pay attention to event-related potentials or EEG spectral content when they diagnose the patient. Since PD is related to brain activities, EEG has great potential in predicting FoG events. Recently, Handojoseno et al.[72] explored the relation between EEG and FoG and reach the result of 75% accuracy, 75% sensitivity, 75% specificity, which shows the potential in FoG prediction.

Electrocardiography (ECG) is the process of recording the electrical activity of the heart using electrodes placed on the skin.These electrodes detect electrical changes on the skin that are a result of blood movement because of heart beat. Since FoG may be related to emotions and moods, ECG has the potential to reveal the connection between FoG and heart signals. Mazilu et al.[74] has explored ECG combined with Skin Conductance signals to predict FoG events and reach an accuracy of 71.3% in classify pre-FoG episodes, which is the first time to employ these signals to compute FoG.

Electromyography (EMG) is an electrodiagnostic medical technique used to evaluate and record the electrical signals generated from skeletal muscle activities. EMG can create an electromyograph to detect the electric potential generated by muscle cells when these cells are electrically or neurologically activated. The signals can contribute to identifying FoG events with learning algorithms [75].

Functional Near-Infrared Spectroscopy (fNIRS) is a non-invasive imaging method that makes the use of near-infrared spectroscopy aiming at functional neuroimaging. Brain activities can be measured and detected by hemodynamic responses and neuron behaviors when applying fNIRS. As we have mentioned, FoG and PD is related to brain activities. Therefore, prior to FoG events, the images of brain activities can have different patterns, which may potentially contribute to FoG prediction. [73] first explore the fNIRS as a sensor to predict FoG episodes and detect the chemicals variation in blood that is related to FoG events.

4. Feature Extraction

Feature extraction is the most critical part of FoG detection and prediction. Because of the differences between sensors, the features extracted may vary. In the feature extraction process, slight changes for each parameter may have a considerable influence on the performance, such as window size, frequency threshold, etc.. Typically, we have time domain features and frequency domain features. Most research utilizes threshold-based algorithms to compute the FoG events on frequency domain features. Some research selects both time and frequency domain features as an input of learning algorithms to detect or predict FoG episodes. First, we present the signal processing techniques used in both the time and frequency domain. Second, we discuss features limited to the time domain. Finally, we examine the features used in the frequency domain.

4.1. Signal Processing Techniques

Before introducing these features, we will briefly go through the signal processing techniques and parameters that have been employed in FoG computing (mainly for motion sensors), which can potentially enhance the sensor signal qualities.

First is the Sampling Rate Selection. Motion sensors such as the accelerometers typically can provide an inertial signal from 64Hz to 256 Hz. For FoG events computing, due to the slow movement frequency, the sampling rates are chosen less than 100Hz, which is enough to compute FoG events. Like, [63] [47] use 64Hz as sampling rate for threshold-based algorithm, while [61] use 40Hz for learning-based algorithm.

Second is the Noise Reduction. The step frequency and frequency of FoG are typically less than 15Hz, which are not rapid movements. Therefore, some researchers utilize a low-pass filter to reduce high-frequency noise. For example, [61] employs a 2^{nd} order Butterworth low-pass filter to gain 15Hz cut-off frequency. Also, removing the outliers can help to reduce the unexpected variance in the signal. Z score and interquartile range (IQR) are two common approaches to remove outliers. Both methods utilize the standard deviation and mean to determine the unexpected points[81] [82].

Third is the Window Size Selection. Initially, Bächlin et al. [63] uses the window size of 4 seconds, and Zach et al. [54] explores that the result works similarly between 2s-4s. Later, [48] verifies that the specificity is very low when it employs a tiny window size, and they suggest working with the window size over 2.5 s. Thus, 2.5s to 4s is a well-selected range of the window size for better performance of FoG computing.

Fourth is Data Imputation. Missing data is not uncommon in raw sensing signals. Data imputation will potentially enhance the FoG computing accuracy. Data imputation [83] [84], including average imputation, regression substitution, and multiple imputation, is a widely adopted method that uses substitute values to replace the lost data. The substitute values can be replaced either by the average values of other participants, the regression estimations, or the regression and correlation predictions.

4.2. Time Domain Features

Different sensors, such as motion sensors and fNIRs will create different time domain features. Typically, for motion sensors and EEG, time domain features are selected as the input to learning algorithms. This is because it is difficult to set any threshold to filter time domain signals into time domain features. As for fNIRs signals, it can show how our brain works and how chemicals react. Therefore, we will introduce the time domain features separately.

For the sensors with electrical signals, we usually extract the features from each window or correlated windows. Next, we will introduce time domain features that have been employed in FoG wearable computing. Take one window x axis reading of an accelerometer as an example, Let $x_w^1, \cdots, x_w^N$ be the time domain samples in the Window W.

1. Mean: The average value of electrical signals in one window. It is related to orientation of the inertial system.

$$\bar{x}_W = \frac{1}{n}\Sigma_{i=1}^{n} x_w^i \tag{1}$$

2. Standard Deviation: The standard deviation of electrical signals in one window. It is related to the intensity of movement.

$$\sigma x_W = \sqrt{\frac{1}{n}\Sigma_{i=1}^{n}(x_w^i - \bar{x}_w^i)^2} \tag{2}$$

3. Increment of one axis: The Increment of different mean values from continuous windows of one axis. It can provide the movement variation within the time of two continuous windows.

$$\delta x_W = x_{W+1} - x_W \tag{3}$$

4. Increment of two axes: The Increment of different mean values from two continuous windows of two axes. It can provide the movement variation between different axes. Take two continuous windows x axis and y axis reading of an accelerometer as an example:

$$\delta \bar{x} y_W = \delta y_{(W+1)} - \delta x_{(W+1)} \tag{4}$$

5. Integral: The Integral of all the values in one window. It is related to the quantity of movements.

$$\hat{x}_W = \int_{i=1}^{n} x_W^i \tag{5}$$

6. Correlation Coefficient: Correlation between each couple of axes. It indicates the linear relation of different directions. Take two continuous windows x axis and y axis reading of an accelerometer as an example:

$$r_W^{xy} = \frac{\Sigma_{i=1}^{n}[(x_w^i - \bar{x}_w^i)(y_w^i - \bar{y}_w^i)]}{n\sigma x_w \sigma y_w} \tag{6}$$

7. Autoregressive Coefficient: The coefficient is the relation between time-shifted version of original version when given the amount of time shift.

$$AC_W^x = arburg(x_W^i, Shift) \tag{7}$$

Other features that may not have apparent relations with movement such as Min, Max, Median, Root Mean Square, Geo Mean, Kurtosis, Skewness, TrimMean, Range, Zero Crossing Rate, Mean Crossing Rate, etc. and certain sensor features such as Signal Magnitude Vector, Average Acceleration Energy etc. have been explored by Mazilu et al.[49]. These features can be further selected by principal component analysis (PCA) and they capture top five to top twenty features with mutual information.

fNIRs images can show chemical variations in the blood. Maidan et al. discovered that HbO_2 changes before and during FoG while turning in PD patients [73]. Specificly, during anticipated turning, HbO_2 increased before FoG and increased more during FoG. During unexpected turning without FoG, HbO_2 decreased. In non-PD patients, HbO_2 does not change during turns. Even though these features can only be acquired in the hospital, it can be more significant in understanding the pathology and FoG intervention compared with other wearable devices.

4.3. Frequency Domain Features

Frequency domain features are dominant indexes for sensors with electrical signals. Step frequency change is an apparent of FoG. This has lead to the deployment of motion sensors in an attempt use this feature to detect and predict FoG. Based on this principle, a well-known frequency threshold algorithm Moore-Bächlin FoG Algorithm, (MBFA) is designed to detect FoG episodes. Later, as learning algorithms are introduced into FoG computing, more frequency domain features are required as the input. Next, we will present various features based on different algorithms.

Before introducing the frequency domain features, we will briefly present the techniques of signal transformation that have been utilized in FoG computing.

First, **Fast Fourier Transforms** (FFT) have been commonly employed in ubiquitous computing to search the distinct dominant frequencies from time-domain signals. It is accessible to combine a Low-Pass Filter to remove the high-frequency noises or a Band Pass Filters to gain target frequency signals. FFT is also a light computing method for time-frequency analysis [85]. In FoG computing, most research with motion sensors utilizes FFT to obtain frequency domain features.

Second, **Discrete wavelet Transforms** (DWT) is a discretely sampled wavelet transformation. Different from FFT, DWT typically can have a high resolution and also can capture the frequency and location in time [86]. [72] applies DWT to analyze the EEG signals and extract the frequency domain features.

Since the threshold-based algorithms have been widely used by many researchers, we will take the most representative one MBFA algorithm as an example to introduce the features. They mainly propose two features [63]:

(1) Freezing Index (FI): The equation for FI is as follows. It is the result of the power spectral density (PSD) from Freezing Band (FB) and the PSD from Walking Band (WB). Typically, FB is from 3 to 8Hz, and the WB is from 0.5 to 3 Hz.

$$FI = \frac{PSD_{3-8Hz}}{PSD_{0.5-3Hz}} = \frac{FB}{WB} \tag{8}$$

(2) Power Index (PI):The euation for Pi is as follows, defined as the addition of WB and FB to determine if there is any relative amount of movement when FI is high. PI also can help eliminate the situations where the patients are not moving voluntarily. In Section 5.1, we will discuss the algorithm into details.

$$PI = FB + WB \tag{9}$$

Some frequency features for learning algorithms are similar to time-domain features such as the standard deviation, kurtosis, skewness. Other frequency domain features demand further computing such as Entropy, Energy, etc. Entropy is the measurement of the distribution of frequency components. Energy is the summation of the squared discrete FFT-component magnitudes of the signal, which is divided by the window length for normalization. [61] [47] [49], have investigated all the features with shallow learning algorithms for FoG detection and prediction.

5. Algorithm

After introducing sensor selection and feature extraction, we present different types of algorithms selected by researchers in FoG computing. FoG computing is focused on classification and prediction of FoG events. To accomplish this, there are two main types of algorithms that are commonly utilized in FoG computing: threshold-based algorithms and learning-based algorithms.

Learning-based algorithms have been widely used recently, and most of the recent research on FoG computing employed the shallow learning algorithm and deep learning algorithm to improve the accuracy of FoG detection and attempt to predict the FoG episodes.

Threshold-based algorithms typically have the following benefits. First, they need less computing resources, which means it can be implemented on smart devices. Second, it does not require massive data samples, and does not need the data augmentations, which reduces the burden of data collection. Third, to promoting the performance of MBFA algorithm a series of research has been working on improving it and testing it with different parameters in alternative environments, which makes it most robust and sound threshold-based algorithm so far.

Learning-based algorithm mainly has the following advantages: First, learning-based algorithm can reach higher accuracy on FoG detection. Second, it has the potential to predict the FoG events hundreds of milliseconds before it happens, while threshold-based algorithm is not able to predict FoG episodes. Third, it can also be implemented in both motion sensors, clinical sensors and other types of sensors.

5.1. Threshold-Based Algorithm

Threshold-based algorithms mainly use frequency features for FoG computing since FoG is related to the step frequency. Before the MBFA algorithm, researchers set a threshold to classify the FoG events based on the heuristic rules, which may cause a series of misclassifications. Later Moore et al. and Bächlin et al. proposed the threshold-based MBFA algorithm to enhance the accuracy of FoG detection.

In 2008, Moore et al. have proposed an algorithm to detect FoG with the accelerometer attached to the ankle. They presented the FI as Eq. (8) to describe FoG episodes. When FI exceed a distinguished threshold, Freezing Threshold (FTH), they classified it as an FoG event. Later in 2009, Bächlin et al. employed the Power Index (PI) as Eq. (9) to address the false positives caused by the rest of the patients. When PI exceeds the Power Threshold (PTH), they identify whether they have a related amount of movement when FI exceed the FTH. In this way, it will eliminate the case where the patients don't have enough movement. Consequently, in the MBFA algorithm, an FoG event will be classified if $FI > FTH$ and $PI > PTH$. So far, this is the best Threshold-based Algorithms for FoG detection due to its excellent performance and less cost of computing [40] [63].

5.2. Learning-Based Algorithm

In the Feature Extraction section, we have mentioned that both time domain features and frequency domain features are selected as the input of learning-based algorithms. Since threshold-based algorithms are limited to computing those features, learning-based algorithms are employed to enhance the performance of FoG detection and prediction. Typically, learning-based algorithms can be divided into two groups: shallow learning algorithms and deep learning algorithms. Next, we will introduce the two groups of algorithms

5.2.1. Shallow learning Algorithm

Shallow learning algorithms mainly have two types: Supervised and unsupervised algorithms. Supervised algorithms are learning the mapping function from input variables to an output variable based on the given pairs of input-output [87]. These algorithms learn from a manually labeled data set. Unsupervised algorithms learn from the input data without any output labels. The goal of unsupervised learning is to model the underlying structure or distribution in the data since it may be difficult to label the data manually or we don't have the classification group.

In FoG computing shallow learning approaches were first employed by Mazilu et al. in 2012 [47] and 2013 [49]. They selected the following classifiers as the algorithm used on the dataset which is based on the motion sensors: Naive Bayes (NB), K-nearest neighbor (KNN), Random Forest (RF), Adaptive Boosting (AdaBoost). Based on their research, RF has the best performance with four seconds windows features as input. Later, Ahlrichs et al. [53]. and Rodríguez et al. [61] mainly utilize the Support Vector Machine (SVM) algorithm to classify FoG events also based on the motion sensors. Next, we are going to introduce each shallow learning method used in FoG detection.

Bayesian Network is a graphical model that can generate the probability for each node and link to process uncertain data. The model represents features as nodes connects them with directional dependency links. Researchers usually employ the model to support decision making or strategy searching when the domain is uncertain or ground truth is difficult to collect [88] [89].

A K-Nearest Neighbors classifier is a machine learning algorithm that employs a probabilistic method to determine classification questions and regression problems. First, the algorithm maintains all samples in the training dataset. Next, the algorithm determines k most similar training samples from each test sample. And then, it picks the most frequently used class label for the test instance. The algorithm can return the mean of the k labels for regression and the most used class of the k labels for a classification problem. Although researchers frequently use a KNN classifier, it is more expensive in computing time than other classifiers [90] [91].

Random Forests is a machine learning algorithm that can create models for both classification and prediction problems. The model employs multiple unpruned decision trees to calculate a target value, which can also avoid overfitting. Although the workload is somewhat expensive, this algorithm can potentially be used to predict FoG episodes [92] [93]. In addition, Random Forests are often used in feature selection, as the tree-based approaches typically rank features by how they enhance the purity of the node. At the top of all trees are the nodes with the most considerable decrease in impurity, while at the bottom of the trees are the nodes with the slightest decrease. Therefore, by pruning trees below a specific node, a subset of the most significant features can be created [94].

Logistic regression is a form of regression analysis modeling the probabilities for binary classification problems. Compared with linear regression, logistic regression can provide probabilities for the classification model. Besides, Logistic regression significantly helps in understanding which independent variables discriminate between the two groups, which can contribute to feature selection [95] [96].

AdaBoost is a method used for classification problems in which a strong classifier is built from a group of weaker classifiers. Based on the first model, it creates a second model to eliminate errors from the training data. The models is continually updated until the prediction is precise enough or maximum models have been employed. AdaBoost works best for binary classification problems [97] [98].

Support Vector Machine has been widely utilized to solve the high-dimensional classification problems. It applies the hyperplanes as the boundaries to separate the data points accurately. There are two rules to choose the hyperplanes: First, the hyperplanes must divide the data points precisely. Second, there must be a maximum potential distance between support vector points and the hyperplanes. SVM is highly acceptive since it can solve non-linear classification problems with less computing workload, which can also be utilized on devices with less computing power [99] [100].

5.2.2. Deep Learning Algorithm

Recently, deep learning algorithms are becoming popular and commonly used in wearable computing. Deep learning algorithms are typically multi-layer neural network architectures similar to that of a natural human. In deep learning, a machine can learn to classify tasks directly from images, dynamic electrical signals, or text. So far, it can achieve state-of-the-art accuracy, even exceeding human-level performance due to the huge computing power. Models are trained by massive labeled data, which is much larger than the amount of data required for shallow learning.

Some research employs the deep learning model in FoG computing in order to enhance the performance of FoG detection and explore the FoG prediction. Mazilu et al. in 2012 [47] has explored the Multilayer Perceptron (MLP) in FoG online detecting. In 2011, Cole et al. [75] first employed the Dynamic Neural Network (DNN) for FoG detection. In 2012, Handojoseno et al. [72] explored Back Propagation Neural Network (BP-NN) based on the EEG signals to predict the FoG events. In recent year, Saad et al.[70] tried the Gaussian Neural Network (GNN) based on multiple motion sensors in FoG detection, while Camps et al. [62] utilized Convolutional Neural Network (CNN) to detect the FoG events. Next, we mainly introduce the most recent used deep learning model MLP, GNN, and CNN.

Multilayer Perceptron (MLP) is a supervised learning approach with fully connected neural network that has been broadly used for solving complex classification problem and parallel processing. MLP is in a directed graph in which the signal path through the nodes only goes one way. Researchers select MLP as the first step of deep learning since the graph is simple, and the workload is less compared with other deep learning algorithms [101], [102].

Gaussian Neural Network is actually the deep neural network with the Gaussian Process. Gaussian Process models a higher abstract of human thought in contrast to human brain modeled by neural network. Compared to conventional deep neural network, GNN is quite tractable and precise, without relying on your training parameter and the input function for convergence [103] [104].

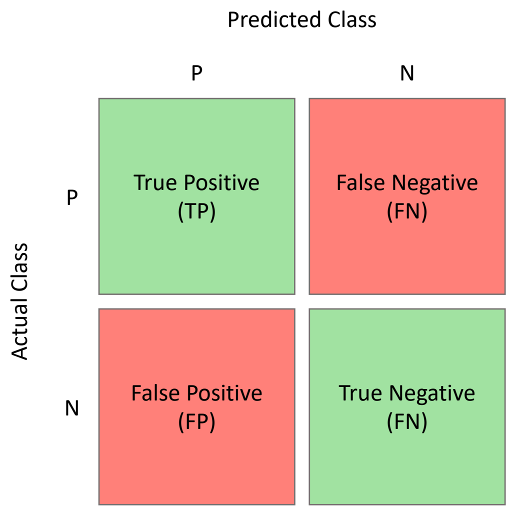

Figure 3: Flowchart of FoG computing

Convolutional Neural Network can refer to a regularized version of MLP, which employs a hierarchical pattern to avoid overfitting. It is a forward feeding deep neural network that contains an input layer, an output layer, and multiple hidden layers. Different from conventional deep learning models that include stacked dense layers, CNN applies an efficient and practical alternative to reduce the overwhelming amount of weights. Recently, CNNs have been extensively utilized in image processing, video processing, and natural language processing where the data is complex and extremely large. In FoG computing, CNN has the potential to predict the FoG events [105] [106].

Recurrent Neural Networks (RNNs), different from traditional neural networks, contain an internal memory that can process sequences of input. RNNs contains loops, which means that the current input and output are learned from previous input allowing to classify and predict current events based on previous ones [107]. Therefore, RNNs, like Long Short-Term Memory (LSTM), are suitable for classifying and predicting time-aware datasets, which makes for excellent potential in FoG computing [108].

6. Performance

Researchers often utilize the performance of FoG computing as the most important criterion to evaluate their system. Typically, we use performance metrics to quantify the accuracy of the system's execution. In this section, We first introduce the implication of performance metrics and how to calculate each parameter. As we have mentioned, FoG computing generally contains FoG detection and FoG prediction. Next, we will present the performance of FoG detection and prediction respectively.

6.1. Performance Metrics

The confusion matrix is an array that stores the results of a classifier. It presents the performance of a learning algorithm as shown in Figure 3. Since FoG detection is a binary classification, typically the result contains True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN). During the evaluation process, two central parameters Sensitivity and specificity are employed to determine the performance quality. The definitions are defined as below:

(1) True Positive (TP): Positive instance that is classified as positive.
(2) True Negative (TN): Negative instance that is classified as negative.
(3) False Positive (FP): Negative instance that is classified as positive.
(4) False Negative (FN): Positive instance that is classified as negative.

Next, we will present the performance indicators which can assess the efficacy of a learning algorithm.

Performance indicators used to evaluate the efficiency of learning algorithms are presented next.

Accuracy is the most commonly used performance indicator. It describes how close the predicted value is to the original and the systematic errors throughout the data. It is defined as Eq. (10):

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

The recall, also known as TP rate or sensitivity, is the number of True Positives over the combination of True Positives and False Negatives. It is defined as Eq. (11):

$$Recall = \frac{TP}{TP + FN} \tag{11}$$

The precision, also known as positive predicted value, is the number of True Positives over the combination of True Positives and False Positives. It is defined as Eq. (12):

$$Precision = \frac{TP}{TP + FP} \tag{12}$$

The specificity, also known as true negative rate, is the number of the True Negatives over the combination of True Negatives and False Positives. It is defined as Eq. (13):

$$Specificity = \frac{TN}{TN + FP} \tag{13}$$

The false positive rate (FPR), is the number of False Positives over the combination of True Negatives and False Positives. It is defined as Eq. (14):

$$FPR = \frac{FP}{TN + FP} \tag{14}$$

F-measure is a way to combine the previous performance indicators for an overall assessment. It is defined as Eq. (15):

$$F - measure = \frac{2Precision * Recall}{Precision + Recall} \tag{15}$$

6.2. Performance of FoG Detection

FoG detection has been explored by many researchers for the recent two decades. They have tested different sensors, classifiers, datasets, window sizes, etc. in order to enhance the performance of FoG detection and increase the convenience of the wearable devices, such as using a smartphone to detect FoG events. Generally, researchers always use accuracy, sensitivity, specificity to assess their system accuracy. However, we believe that the time delay is also an index which we need to pay attention to though many researchers ignore to mention it. Because time delay may have an influence on the FoG treatment, such as when will the rhythm cueing start or warning the patients from falling. In Table 3, we show the Reference, Sensors, Classifiers, PD patients, Time Delay, and Performance for each FoG detection application. This table mainly summaries previous work on FoG detection. Since all these works have different experiment settings, the performance is not comparable.

First, most papers choose motion sensors to detect FoG events, and the result of them are much better than other sensors like EEG and EMG since motion sensor signals are more directly related to FoG events. Therefore, to detect FoG, motion sensors especially the accelerometer is the best choice so far both on performance and practicality. Next, we can discover that the performance of learning-based classifiers is typically better than threshold-based ones. It is not difficult to understand since learning-based classifiers employ more features and more massive computing resources. So far, the deep learning based algorithms [62] perform best with the sensitivity of 91.9% and specificity of 89.5% (Performance of [47] is under special conditions). Besides, the dataset of PD patients is generally less than 30 since it is challenging to collect data of randomly occurring events from PD patients. Also, even though many papers do not mention the time delay of FoG detection, we still consider this as an essential performance index, which can determine the efficacy of the just-in-time intervention. So far, the time delay is typically less than 500ms with certain classifiers. However, as we utilize more sophistical classifiers and algorithms, the time delay will undoubtedly increase, which decrease the significance of FoG detection.

Table 3: **Performance for FoG Detection**

References	Sensors	Classifier	PD Patients	Time Delay	Performance
[40]	Motion Sensor	Threshold-based	11	N/A	Accuracy: 89.10%
[41]	Motion Sensor	Linear Classifier	2	N/A	Accuracy: 82.70%
[42]	Motion Sensor	Threshold-based	1	Avg: 332ms Max: 580ms	Accuracy: 78.00%
[78]	Motion Sensor	Threshold-based	10	N/A	Sensitivity: 75.00%-83.00% Specificity:95.00%
[75]	Motion Sensor & EMG	Dynamic Neural Networks	10	N/A	Sensitivity: 83.00% Specificity:97.00%
[43]	Motion Sensor	Threshold-based	6	N/A	Sensitivity: 88.30% Specificity:85.30%
[45]	Motion Sensor	Threshold-based	8	N/A	Sensitivity: 81.70% Specificity: N/A
[72]	EEG	BP-NN	26	N/A	Sensitivity: 74.20% Specificity:78.90%
[47]	Motion Sensor	Learning-Based	10	Avg: 340ms Max: 710ms	Sensitivity: 95.00% Specificity:95%
[48]	Motion Sensor	Threshold-based	25	N/A	Sensitivity: 86.80% Specificity:82.40%
[64]	Motion Sensor	Learning-based	5	N/A	Accuracy: 96.11% Sensitivity: 81.94% Specificity:98.6%
[54]	Motion Sensor	Threshold-based	23	N/A	Sensitivity: 75.00% Specificity: 76.00%
[53]	Motion Sensor	Learning-based	8	N/A	Accuracy $>$ 90.00%
[69]	Motion Sensor	Threshold-based	5	$<$ 500ms	Sensitivity: 97.00% Specificity: N/A
[56]	Motion Sensor	Threshold-based	10	N/A	Best: Sensitivity: 84.90% Specificity: 81.00%
[66]	Motion Sensor	Learning-based	15	N/A	Best: Sensitivity: 86.00% Specificity: 92.00%
[59]	Motion Sensor	Threshold-based	10	N/A	Sensitivity: 73.10% Specificity: 81.60%
[60]	Motion Sensor	Threshold-based	20	N/A	Sensitivity: 87.57% Specificity: 94.97%
[61]	Motion Sensor	Learning-based	21	N/A	Sensitivity: 88.10% Specificity: 80.10%
[62]	Motion Sensor	Deep Leanring	21	N/A	Sensitivity: 91.90% Specificity: 89.50%
[109]	Motion Sensor	Learning-based	10	N/A	Sensitivity: 92.40% Specificity: 94.90%
[110]	Motion Sensor	Learning-based	4	N/A	Accuracy: 94.40%
[111]	Motion Sensor & EMG	Deep Learning	4	N/A	Accuracy: 96.30%
[112]	Motion Sensor	Deep Learning	5	N/A	Accuracy: 99.38% Sensitivity: 97.50%
[113]	Motion Sensor	Learning-based	16	N/A	Accuracy: 81.30%
[114]	Motion Sensor	Deep Leanring	10	N/A	Sensitivity: 96.10% Specificity: 95.50%
[115]	Motion Sensor	Leanring-based	63	N/A	Sensitivity: 95.60% Specificity: 90.20%
[116]	Camera	Deep Leanring	45	N/A	Accuracy: 82.50%
[117]	Motion Sensor	Learning-based	18	N/A	Sensitivity: 95.80% Specificity: 95.00%

6.3. Performance of FoG Prediction

Different from FoG detection, FoG prediction applications are in the exploration stage. Researchers tested various sensors, features, and algorithms to try to create a system to solve this problem. So far, even though some systems have been built to predict FoG events, the performance is not as accurate as FoG detection. This is mainly due to the lack of information on the mental causes of FoG and non-physical symptoms before FoG. Researchers employ EEG, fNIRs, ECG, Skin Conductance to predict the FoG episodes. These signals are monitored with clinical sensors to predict FoG even though they are obtrusive and inconvenient. Next, we will use Table 4 to summarize explorations that contribute to FoG prediction.

Table 4: **Performance for FoG Prediction**

References	Sensors	Classifier	PD Patients	Performance
[49]	Motion Sensors	Learning-based	10	F-measure=56.00%
[74]	ECG + Skin Conductance	Threshold-based	18	Accuracy: 71.30%
[73]	fNIRs	N/A	22	N/A
[118]	EEG	Learning-based	26	Sensitivity: 83.50% Specificity: 60.50%
[119]	EEG	Learning-based	16	Sensitivity: 60.80%-86.00% Specificity: 66.13%-82.89%
[120]	Motion sensor	Learning-based	12	Accuracy: 82.7%

In Table 4, we can discover that clinical sensors perform better than motion sensors. The performance is very intuitive that before FoG happens, there is no movement features for motion sensors to capture. Even though the performance of clinical sensors are still from 60% to 86%, it is a good start for researchers to work on FoG prediction with different sensors. fNIRs are a new way that could predict the FoG in the future with new classifier.

7. Challenges and Future Trends

Existing FoG computing mainly focuses on FoG detection and researchers are able to achieve a high-performance on it. Future FoG computing could pay more attention to FoG prediction, which is valuable to prevent PD patients from falling or other physical damage. This section presents the challenges and future trends for both existing and future FoG computing.

7.1. Challenges for FoG Computing

The future of FoG computing is still confronted with many challenges, such as data collection, and time latency for FoG detection, and FoG prediction. These challenges may still be a research topic in the near future. Next, we present the challenges and possible solutions for FoG computing.

Challenges for Data Collection: Data collection for FoG computing is a challenge both for existing and future research. First, PD patients are typically senior people who are not always available to collaborate with researchers for data collection. Second, FoG events occur randomly, so it is hard to control the data collection process. To increase the chance of FoG occurrence some researchers create narrow spaces for PD patients to walk through. However, researchers purposefully creating FoG events is still limited and not always friendly to PD patients. Therefore, data collection for FoG computing is a time-consuming and challenging process. DAPHNET is an open source dataset containing data from three acceleration sensors placed at the hip and leg and labelled to reflect FoG occurences [59]. While some researchers have explored this dataset with different classifiers, it still has the potential to be explored in the future.

Challenges for reducing the time latency of FoG detection: Even though the performance for FoG detection is efficient and significant, the time latency is still around 350-500 milliseconds. Since FoG is dangerous and poses a threat to PD patients' lives, the time between the FoG occurrence and detection should be as short as possible. Due to the time latency, FoG can still cause a falling or other physical damage to PD patients, which lower the significance of FoG detection. FoG detection is supposed to contribute to FoG intervention and treatment. No matter how accurate the detection of FoG events, more time is necessary to prevent PD patients from getting hurt or falling. Time latency is typically related to the hardware and signal transmitting and signal processing. It could be improved if we upgrade one of them to be faster.

Challenges for unbalanced data: Unbalanced data refers to the problem in which the dataset contains uneven examples. It is an especially common problem when researchers process FoG data, as FoG episodes comprise a relatively small set compared to healthy control samples. The unbalanced data can be a problem in machine learning algorithms. Suppose we have 5 FoG events and 95 healthy episodes: the machine learning model could predict all the samples to be healthy ones, and the accuracy would still be 95 percent. Typically we have two simple approaches to deal with the problem: under-sampling and over-sampling. With under-sampling, we can randomly choose the number of healthy samples and make them match the number of FoG cases. However, the model may lose some relevant information because we have discarded samples. With over-sampling, we can randomly duplicate some FoG samples and make them match the number of healthy cases. However, this may lead to an overfitted model and an overestimation performance. There is a trade-off between the two resampling methods, and this problem needs to be better addressed in the future.

Challenges for FoG prediction: FoG prediction is a better choice for the intervention or treatment of FoG compared with FoG detection. Predicting hundreds of milliseconds before FoG occurrence can make a significant difference. However, so far, FoG prediction is still limited to obtrusive and inconvenient clinical sensors, which is not applicable to the home environment. As researchers have discovered, FoG is relevant to physiological signals, such as heart rate, and skin conductance, which could be combined with motion sensors to predict FoG events.

7.2. Future Trends

The future trends for FoG computing will likely be associated with FoG prediction. Therefore, we propose some possible trends that can contribute to the advancement of FoG prediction.

Using domain knowledge for prediction: Researchers have explored motion sensors and clinical sensors for the FoG prediction. Even though it shows promise for the prediction of FoG events, the accuracy is limited. Therefore, employing health domain knowledge may potentially contribute to the performance of FoG prediction. Also, exploring new sensors which are related to human physiological signals, such as fNIRs, skin conductance sensors is also a future trend.

How to make it less intrusive: Researchers have employed wearable devices and smartphones to detect FoG in home environments. However, so far, only clinical devices are able to predict FoG, which are intrusive, unportable and unable to commercialize. Therefore, how to make the devices less invasive is a future trend. Researchers can employ wireless sensing such as WiFi-sensing, RF-based Sensing, Acoustic-based sensing or other smart device to address this challenge.

Just-in-time intervention: The goal of FoG computing is to treat or mitigate the FoG just-in-time. Therefore, how to deal with the time delay for FoG detection or predict a period of time earlier before the FoG happens are the future trends. Currently, researchers utilize rhythmical cueing and step-synchronized vibratory cueing to mitigate FoG, which is still in the early stages of research. Therefore, it is a future trend that researcher can develop efficient and portable just-in-time intervention device for PD patients.

Deep learning features: The deep learning features are difficult to understand intuitively by clinical researchers since those features are not directly related to disease symptoms. It is important that researchers can visualize deep learning features so that they can be better understood. It is a trend for clinical researchers to cooperate with data science and computer science researchers on FoG computing and other smart health research.

8. Conclusion

This paper gives a survey of background knowledge, related work, sensor selection, feature extraction, algorithms, and performance results of FoG computing. It presents the basic concepts, advantages, limitations and use cases of different approaches. Besides, the survey highlights three FoG computing challenges: Data collection, Time latency reduction, and FoG Prediction in FoG computing. Finally, we propose three future trends: FoG prediction, Just-in-time intervention, and how to make it less intrusive, for improving existing FoG research.

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