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Computer-Vision Based Diagnosis of Parkinson's Disease via Gait: A Survey

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ABSTRACT Parkinson's Disease (PD) being the second most hazardous neurological disorder has developed its roots in damaging people's quality of life (QOL). The ineffectiveness of clinical rating scales makes the PD diagnosis a very complicated task. Thus, more efficient systems are required to perform an automated evaluation of PD for its earlier detection and to enhance life expectancy rate. Gait based clinical diagnosis can provide useful indications regarding the presence of PD. From recent years, computer vision-based (VB) analysis is in great demand and seems to be highly effective in PD inspection. The objective of this article is to systematically analyze the applications of computer vision in PD evaluation through gait. This paper surveys the VB PD gait acquisition modalities as well as provides a concise overview of preprocessing techniques. The study presents a description of PD related gait features, extraction and selection methods used for PD analysis. A number of machine learning techniques for classification of PD and healthy gait are also discussed. This article extensively surveys PD gait datasets considering data from 1997 to 2018. Also, several research gaps in existing studies have identified that need to be addressed in the future. At last, an outline of the proposed idea is given that can cope up with the related issues and can lead to quality VB PD gait investigation.

INDEX TERMS Parkinson's disease, acquisition modalities, gait features, extraction methods, vision-based.

I. INTRODUCTION

In the present era of remarkable technological advancements, identification of an abnormal health condition is of highest concern. Over past years, the unique characteristics of the human body known as biometric (e.g. handwriting [1], speech [2], gait, etc.) have been enormously analyzed to make excellent progress in clinical diagnosis. Each individual has an idiosyncratic style of walking that occurs due to coordinated and collaborated actions of the musculoskeletal and nervous system. This makes the gait biometric a powerful indicator to determine pathological behavior caused due to physical injury, aging or related disorders [3], [4]. These internal and external factors directly affect the motion and action of the body and results in gait impairment. Neurological disorders (ND) have been discerned as one of the prevailing conditions causing high burden to the large population. The data on 'Burden of Disease' by Roser and Ritchie [5] from (1990- 2016) reveals such prevalence among seven continents of the world shown in Fig.1, where the highest growth rate is seen in Asia.

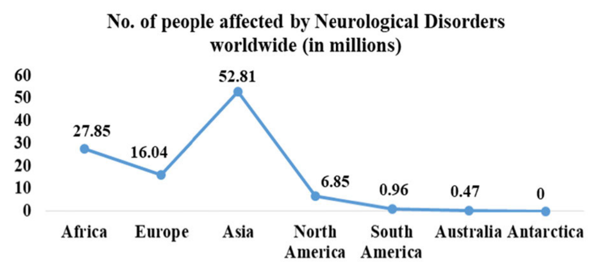

FIGURE 1. ND prevalence in the world's seven continents taken from the study [5]. Here 0 value for Antarctica indicates unavailability of related data.

An analysis by a study [6] to systematically analyze the global burden of 328 diseases has indicated the rise in ND from 14.5% to 18.3% between 2006 and 2016. Other estimates have shown neurological disorders as the major cause of 'Disability Adjusted Life Years' (DALYs) and second utmost leading source of deaths (9.0 million) in 2016 [7]. A number of such disorder exists (such as Alzheimer's,

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Parkinson's, stroke, cerebral palsy, etc.) that are chiefly damaging the people's quality of life (QOL) and causing deaths. Amongst all the ND, this article focusses the study of Parkinson's disease due to its higher growth estimations in the future (almost by double) with the rise in aging society.

Parkinson's disease (PD) is currently the second most common neurogenerative and movement disorder after Alzheimer's disease, affecting about 7-10 million lives worldwide [8]. Although the actual causes behind PD are unknown the related research indicated genetic vulnerability and environmental factors to be responsible for its occurrence. Loss of dopaminergic neurons in the brain seems to be the root cause that leads to the development of PD related symptoms including tremor, movement slowness, postural imbalance, gait deflects, etc. The alterations in a person's gait (e.g. slow speed, freezing of gait (FOG), falls, short steps, etc.) provides significant clues regarding the presence of PD. This disease is primarily related to the age where the symptoms continue to worsen with time (1%-2% over 60 year's adults and increases with age as 3%-5% over 85 years) [9], [10] and adversely attacks male population than females (1.5: 1.0). The subjective diagnosis of PD at early stages using clinical rating scales is very challenging as the symptoms appear more with increased age due to which several cases go unrecognized. Also, there is no cure exists to permanently treat PD but the patient can only rely on medications to control PD symptoms. Every year, about €7000- €17000 have been spent on PD treatment per patient [11] and further rise has been estimated. Therefore, effective and automated analysis of an individual gait parameter's (such as step length, stance phase, speed, etc.) is required to differentiate PD and normal subjects and to provide them rehabilitation.

In recent years, an increase in computer vision-based (VB) gait analysis has been observed, primarily focusing on the automatic diagnosis of PD. Verlekar *et al.* [3] and Ortells *et al.* [12] developed a vision-based automated system and extracted gait features from the human body silhouette. They successfully demonstrated the uniqueness of gait patterns in recognition of PD individuals.

The use of the Kinect sensor by various researchers [13]–[15], etc. to perform gait based automated analysis of PD contributed a lot to this field. Also, some universities played their role by building the VB gait datasets including impaired and normal gait patterns such as INIT (LABCOM, Univ. Jaume I) [12] which has public access to the researchers to explore more in this area. Although having a plethora of advantages for VB gait recognition in PD assessment, certain issues have been confronted by researchers such as unavailability of actual patients vision-based gait database, limited size of samples [16], overlapping [12], poor preprocessing [3] etc. that have opened new scope of research for more unfailing PD analysis.

Research concerning PD inspection includes some surveys performed by different researchers and have given crucial reviews related to it. Recently, a survey by Pereira *et al.* [17] focused on computer-assisted technologies for diagnosis and treatment of PD including speech, handwriting, face images, gait and sensor signals. Another review by Pasluosta *et al.* [18] explored existing wearable technologies and IoT in PD detection. A brief description of the most significant survey articles till Feb. 2019 is provided in Table 1.

This article performed a systematic search of the existing literature to gather the data from reputed journals and conferences. Applying a number of search keywords yielded about 1500 related articles out of which 71 relevant articles that mainly focused on gait based PD detection using vision-based technology are selected after illuminating the irrelevant and duplicate ones.

The motive of this survey article is to systematically study all the facets of PD based on vision-based gait analysis. The principal objectives of the study can be interpreted via points under:

1) This article comprehensively provides a vision-based literature survey of Parkinson's disease based on gait.
2) Scrutinized more than seventy articles of scientific journals and conferences of repute focusing VB that is not explored in existing surveys.
3) The article thoroughly reviews the VB PD gait acquisition modalities and also provides a brief overview of sensor-based modalities emphasizing their issues and possible solutions.
4) The article presents an insight towards data preprocessing techniques used to refine PD data.
5) The paper broadly surveys the gait features as well as feature extraction/selection methods for PD investigation.
6) The paper extensively outlines the machine learning techniques for the diagnosis of PD
7) The article provides a brief description of available gait datasets that can be useful for further PD research.
8) The article explores the open research challenges in the form of future perspectives that need to be focused for accurate PD gait identification.
9) A short illustration of the proposed work is also discussed in section 7.

The organization of the article is as follows: Section 2 provides an overview of human gait basics and PD. The general PD gait recognition framework, gait acquisition modalities, and preprocessing techniques explained in Section 3. Section 4 describes PD gait features and related extraction/selection methods. Section 5 defines machine learning approaches and PD gait datasets outlined in Section 6. Future perspectives and proposed work presented in Section 7 and Section 8. Finally, Section 9 provides the conclusion of this survey article.

II. HUMAN GAIT AND PARKINSON'S DISEASE

The gait of a human being can be visualized as a vital activity to analyze several abnormal health conditions. In-depth analysis of a person's gait plays an important role in diagnosing a number of life-threatening pathologies such as Parkinson's Disease (PD), thus effective in clinical applications.

TABLE 1. Shows some important survey papers on PD gait analysis along with no. of citations.

Author/Year	Key Focus	No. of citiations
Rey et al. [11]/ 2019	They systematically reviewed the existing literature on mobile phone applications used for PD analysis	4
Pereira et al. [17]/ 2018	They focussed recent technologies applied to aid PD considering image and sensor data. They also outlined feature extraction methods, datasets and machine learning algos used in PD inspection	7
Benson et al. [19]/ 2018	The purpose of this study was to review the effectiveness of wearable sensors in external environment and also discusssed the features extracted for PD evaluation	16
Ossig et al. [20]/ 2016	This article extensively reviwed the enabling wearable sensor based technologies for investigation of motor PD symptoms	40
Pasluosta et al. [18]/ 2015	They reviewed the emerging wearable technologies and also discussed the IOT platform that can be useful for PD diagnosis and effective treatments of PD patients	79
Stamford et al. [21]/ 2015	This review focussed the advances in non-locomotion based technologies, their benefit in PD analysis and oulined the issues need to handle in PD	31
Chen et al. [9]/ 2013	They examined the potential of laboratory and wireless sensor based PD gait analysis and also suggested some treatment strategies for PD quality of life	45

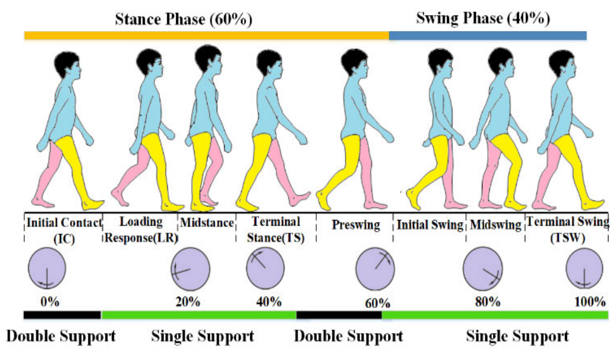


FIGURE 2. Phases of human gait cycle taking right leg (yellow color) as perspective [22].

This section provides a brief description of phases that take place during human gait as well as a short detail of PD, its associated symptoms and clinical measures.

A. BASICS OF HUMAN GAIT CYCLE (GC)

When walking occurs, both the limb of the human body works in an identical way where the left limb acts as a pillar to the right limb and vice-versa [12]. This symmetrical sequence of limbs from first heel-strike/ initial contact (IC) to next heel-strike i.e. terminal swing (TSW) by the same limb happens in the form of a cycle, known as gait cycle (GC) shown in Fig. 2. Generally, there are two common phases that complete total gait cycle [22] - stance phase (orange color) that begins with initial contact indicating that foot is in total contact with the ground and swing phase (blue color) signifying that the foot leaves the floor and swaying in the air. According to Perry and Bumfield [23], these phases are further classified into eight sub-phases where the first five are associated with stance phase contributing 60% to the gait cycle. The other three sub-phases are of swing phase sharing 40% to the total gait cycle. Each phase is responsible for the accomplishment of three significant tasks- weight acceptance (WA), single limb support (SLS) and limb advancement (LA) [24], [25]. Fig.2. depicts the distribution of complete gait cycle considering the right leg as perspective.

The locomotion of a person can be thought of similar to the motion of a wheel, rotating from left to right. As visualized in Fig.2 first snapshot of the wheel is indicating just the start of the gait cycle (IC), initially at 0%. As the wheel moves forward in the clockwise direction, it covers every 20% of the GC by rotating through 72 degrees. This rotation of wheel depicts the occurrence of different sub-phases of GC. The last snapshot of the wheel represents the completion of the GC (100%) [22]. Out of the entire GC, first and fifth sub-phase stipulate the period of double support (black color) and single support period (green color) can be seen from second to fourth and go on from fifth to eighth sub-phase.

Although having different walking patterns, the procedure of ambulation is alike in all the human being [26]. Various gait-related parameters such as step length, cadence, symmetry, etc. can be effectively utilized in order to measure differences among individuals. In a healthy person's gait, cadence (number of steps taken in unit time) is about 120 steps per minute [27] and also the two limbs are symmetrical but it is not the case with an abnormal gait. In PD, the walking characteristics of an individual vary to a larger extent as compared to a normal one such as slow speed, increased cadence, gait asymmetry, etc. [28]. Thus the phases of GC provides decisive clues regarding abnormal motion pattern of a PD subject to better classify an affected gait from a healthier one.

B. OVERVIEW OF PARKINSON'S DISEASE (PD)

The most common degenerative neurological disorder occupying the second place next to Alzheimer's disease i.e. Parkinson disease came into light after being described by a physician, James Parkinson in 1817. PD is a chronic disorder that progresses gently with time and has more life risk on the male population than females [17], [29]. PD being a syndrome of the nervous system directly affects the functioning of the brain and results in loss of neuromuscular control [30]. An area in the human brain named as substantia nigra consists of dopaminergic neurons (transmitter neurons) that releases dopamine chemical to basal ganglia (receptor cell) as shown in Fig.3.

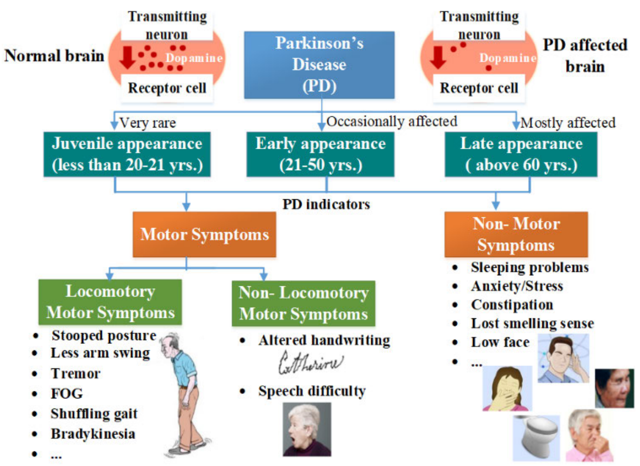


FIGURE 3. A pictorial depiction of a normal brain (left) and PD affected the brain (right) along with its associated symptoms [10], [21]. Some of the images in this and other figures used in the article are taken from the internet. URL's are given in the Appendix.

These basal ganglia have the responsibility to perform the overall integrated functions of the body. In PD, the amount of dopamine chemical produced get reduced due to degeneration of dopamine neurons thereby diminishing the functioning of basal ganglia. As a result, symptoms start appearing indicating the presence of PD [17], [31].

However, the underlying cause of PD is unknown but some factors such as genetic (gene mutations), environmental conditions (pesticides exposure), medication and aging can be regarded as its major contributors [31], [32]. More likely, the average age of people being diagnosed with PD is approximately 60 years, known as 'late-onset' but sometimes it can appear untimely. In some people, the symptoms of PD seen to be developed before the age of 50, known as 'early onset' and very rarely its effect can be visualized on young people less than 21 years too, referred to as 'juvenile-onset' [10], [29]. PD doesn't occur rapidly but starts with some initial symptoms and increases gradually. On being attacked by PD, a person develops typically two types of symptoms i.e. motor (influences movement) and non-motor (no effect on movement) [31] as presented in Fig.3. Motor symptoms further involve Locomotory such as tremor (shaking of the body), bradykinesia (slow movements), postural instability (stooped), altered gait (freezing, shuffling), etc. and non-locomotory motor symptoms including altered handwriting and speech. Non- motor symptoms such as anxiety, constipation, smelling loss etc. also gives the strong evidence of PD occurrence but are often ignored by the doctors [21], [33], [34].

Thus the combination of motor and non- motor symptoms represent the initiation and development of PD deteriorating people lives badly.

1) PD CLINICAL MEASUREMENTS

PD affects in a different way to different people depending upon its progression stages- mild, moderate and advanced. Their relative symptoms are defined in Table 2. Clinical diagnosis of PD heavily relies on conducting various tests such as cerebrospinal fluid test and using neuroimaging techniques (MRI, EEG, etc.) in order to assess subject's motor symptoms and then grading the severity of disease by the clinician on some rating scale [34]. There are numerous PD severity rating scales and questionnaire's available such as Berg Balance Scale (BBS), FOG-Q, Hoehn and Yahr scale (H&Y), Unified Parkinson's disease rating scale (UPDRS) etc. Amongst the mentioned, clinicians mostly prefer the UPDRS scale (a four-point scale) to rate PD severity due to its overall superior clinometric features than other scales [35], [36].

TABLE 2. Different stages of PD severity and related symptoms [32], [34].

PD Stage	Related Symptoms
Mild (early PD)	• Unilateral movement symptoms • Posture and facial expressions alteration • Little walking problem
Moderate	• Bilateral movement symptoms • Freezing of gait (FOG) events • Balance difficulty
Advanced (severe PD)	• High walking trouble • Requires others support

Although using subjective clinical measures for PD evaluation offer less complexity and more easiness but the diagnostic validity and reliability get compromised. The symptoms reported by the patient need not to necessarily correlate with rating scales outcome. Thus, high-level quantitative assessment such as gait measurements should be given attention to enable early PD diagnosis and more effective treatments.

III. GENERIC FRAMEWORK FOR VISION-BASED (VB) PD DIAGNOSIS

The architecture of any diagnostic system represents the chain of interconnected units working in coordination with each other to generate the desired outcome. This section thoroughly describes the main modules of PD diagnosis system highlighting the work in previous studies made by different researchers. The basic pipeline for identification of PD includes five key stages i.e. (I) PD gait acquisition (II) Data Pre-processing (III) Feature extraction and selection (IV) Classification (V) Result is depicted in Fig. 4.

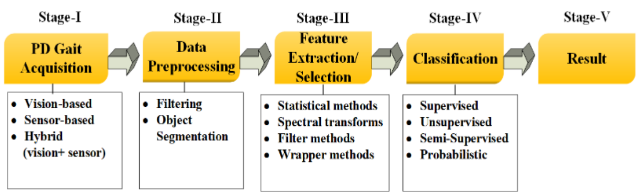


FIGURE 4. **A Representation of diagnostic process workflow for PD recognition.**

Firstly PD and healthy subject's gait data is captured using some modalities and then the acquired data is pre-processed to prepare it for further processing. After initial preprocessing, relevant features are extracted from gait frames. These features then provide a decision regarding normal and abnormal gait. Finally, classification is performed to classify the subjects into PD and healthy group. The complete explanation of each stage is given as follows:

A. PD GAIT ACQUISITION MODALITIES

Data acquisition specifies the task of gathering useful information by applying different sources. The performance of the system entirely depends upon the quality of data captured so utmost care should be given while doing it. To enable the process of data collection, a modality plays a vital role which is simply the agglomeration of devices/ technologies having powerful capturing capabilities. The use of modality can be seen in various areas but it revealed its extensive contribution towards analyzing and collecting gait data of PD affected population.

In this section, a meticulous survey of PD gait capturing modalities has been performed and accordingly, a taxonomy is proposed as illustrated in Fig.5. The studies by various researchers based on this proposed taxonomy are recapitulated in Table 3 from 2005 to Feb. 2019. Broadly, there are two types of PD gait acquisition modalities namely vision-based (VB) and sensor-based (SB). In this article, the key focus is devoted towards only vision-based modality i.e. marker-based (VBMB), marker-less (VBML) (solid color box) used either individually or in-fusion (MB, ML). Since this study covers each and every aspect of vision-based PD detection so it is required to consider those papers also that have collected the PD gait data using sensor and vision-based modalities simultaneously. Further, the articles that focused only sensor modality (shaded box) in Fig.5, for PD gait collection are not considered.

1) VISION-BASED (VB)

A modality that fundamentally relies on the use of opto-electronic motion capture (Mocap) systems to inspect the gait of an individual, is typically referred to as vision-based modality. The concept behind the VB modality is similar to the functioning of the human eye. Using only our naked eyes to analyze someone's gait seems to be an impractical task thus a more robust camera-based system is demanded. This modality consists of employing different type of cameras (e.g. analog, digital, depth) to estimate the human gait accurately [37], [38]. VB modality further involves two sub-categories namely marker-based and marker-less/ appearance based [3].

a: MARKER-BASED (MODEL- BUILD)

As the name suggests, marker-based (MB) modality (emerged between 1960-1984) depends on the use of a number of motion capture camera systems such as 3D Mocap system, Vicon, IR cameras, etc. These are also used along with retroreflective markers (Murray, 1960's-1970's) [39] to improve the accuracy of gait acquisition [3]. In this modality, the model of the human body is constructed manually to extract relevant features. One of the common examples of such systems is Vicon (1984) [40]. Vicon directly builds the human model specifying the anatomical landmarks position on the body skeleton and provides useful gait parameters such as joint angles, by examining the location of body key points obtained through reflective indicators [41].

Retroreflective markers thus employed may be passive or active [25]. Passive markers are generally coated with the layers of reflective material so that whenever light emitted from LED's equipped camera falls on it, the reflection from only those spheres come back, giving the position of body landmarks [42]. In a variation, active markers are LED's itself that are fixed with the subject's body and infrared (IR) waves are discharged by the camera capture the joint points on the body.

Roiz *et al.* [43] proposed a study to analyze the differences among gait parameters of subjects with 12 idiopathic PD and 15 healthy controls using 3D human motion analysis system with six IR cameras and eighteen active markers. The study outcomes demonstrated notable differences between PD patients and healthy subjects and gait variables shown correlation with clinical measures.

In another study, Zhang *et al.* [44] developed a framework to analyze, extract and compare the gait features of 6 PD patients while walking under three different conditions- without any support, roller walker pushing and holding a powered walker in different speeds. The study made use of nine Vicon Mocap system camera and a set of reflective markers to determine the location of the body landmarks. Results indicated a significant decrease in asymmetry index from 6.7% to 0.56% under the first condition and much lower under third one showing the potential of the motorized walker in providing gait symmetry to patients attacked by PD. The use of stereoscopic vision recording setup (two Panasonic (NV-GS500) camcorders (25 frames per second (fps)) having resolution of 720*576 and reflective markers) was employed in a work by Pachoulakis [45] to represent the Kinesiological

TABLE 3. Shows vision-based gait acquisition modalities used for PD analysis with their respective pros and cons.

S.No.	Sensing mode	Mechanism	References	Pros/Cons	Remarks
1	Vision Based Markerless (VBML)	Video cameras (2D/3D, HD, CCD, camcorders, smartphone)	[3,16,48,49,50,53,69,74,76,77,80,86,93,94,97,98,105]	(+) Highly compact (+) Portable and more convenient for recording (+) No requirement of heavy lab. setup (+) Cost effective (-) Less accurate (-) Requirement of trained experts (-) Difficult to interpret images from acquired videos	Vision based markerless modality provides more simple, affordable and easy way to capture gait data for efficient PD diagnosis
		Microsoft Kinect Sensor (MSK)	[12,13,14,15,51,52,54,72,73,78,90,95,106,107,108,109,110,111,112,113,114]	(+) Portable (+) Low error rate (+) Captures 3D motion of entire body (+) Provides depth information of subject's gait (+) Eliminates markers placement complexity (-) Sensitive to sunlight (-) Unsuitable for highly reflective objects detection	
2	Vision Based using Markers (VBMB)	3D Mocap systems (Vicon based on reflective markers, BTS)	[13,43,44,45,46,47,54,80,91,96,104,111,115,116]	(+) Highly accurate (+) Provides exact location of body landmarks (+) Powerful architecture and processing algorithms (-) Expensive (-) Need of high technical skills (-) Requires heavy lab setup to capture gait	These optoelectronic systems acts as 'gold standard' and have high potential for measurement of gait parameters for PD investigation
3	Paired (SB, VB)	FLS, VB	[79,81,83,88,92,117,118,119,120,121]	(+) Simple and easy data analysis (+) Captures foot pressure and forces efficiently (-) High power requirements (-) Requires large space and have massive size (-) Requires exact foot and plate contact for accuracy	Allows simultaneous acquisition of multiple gait parameters for PD detection with more accuracy
		IS, VB	[35,68,71,75,82,87,122,123,124,125,125,126,127]	(+) Provides direct estimation of acceleration, velocity (+) No need of controlled environment (+) Allows long term monitoring at home also (-) Wearing discomfort (-) Accumulated error issue (-) High power consumption (-) Uses complex algos to estimate gait parameters	
		EMG, VB	[70]	(+) Provides measurements of body muscles activities (+) No need of controlled environment (+) Allows long term monitoring for patients (-) Causes pain while wearing (-) High power consumption (-) Requires high skills in electrodes setup	

state of a PD subject at a given time. Results indicated a high potential of the adopted system for PD measurements. Again, an 8-camera Vicon system and reflective markers were utilized in Ref. 46 to investigate the statistical dissimilarities among PD and HC.

Thus, employing this type of modality can lead to a substantial rise in system's performance by giving the exact location of body landmarks essential in PD detection.

b: MARKER-LESS (MODEL-FREE)

One of the unique characteristics of marker-less (ML) modality also referred by its name i.e. appearance-based modality is the non-requirement of manually building the model of the human body to extract the gait parameters. This modality simply relies on capturing the gait of subjects using a single camera. ML modality came into presence with the development of a new camera system's (e.g. Kinect v1, v2, camcorders, smartphones, etc.) during (1995-2011). Usually during walking, initially the gait videos of the people are recorded by a camera device and silhouettes are extracted using some pre-processing techniques (e.g. background subtraction) [3], [48]. Finally, statistical information and other biomechanical features are derived directly from gait image without any prior familiarity about the subject's body [41].

The video-based cameras such as 2D/3D, CCD, etc. played a crucial part in vision-based markerless (VBML) gait collection in PD analysis. Shaw [49] proposed a study to inspect

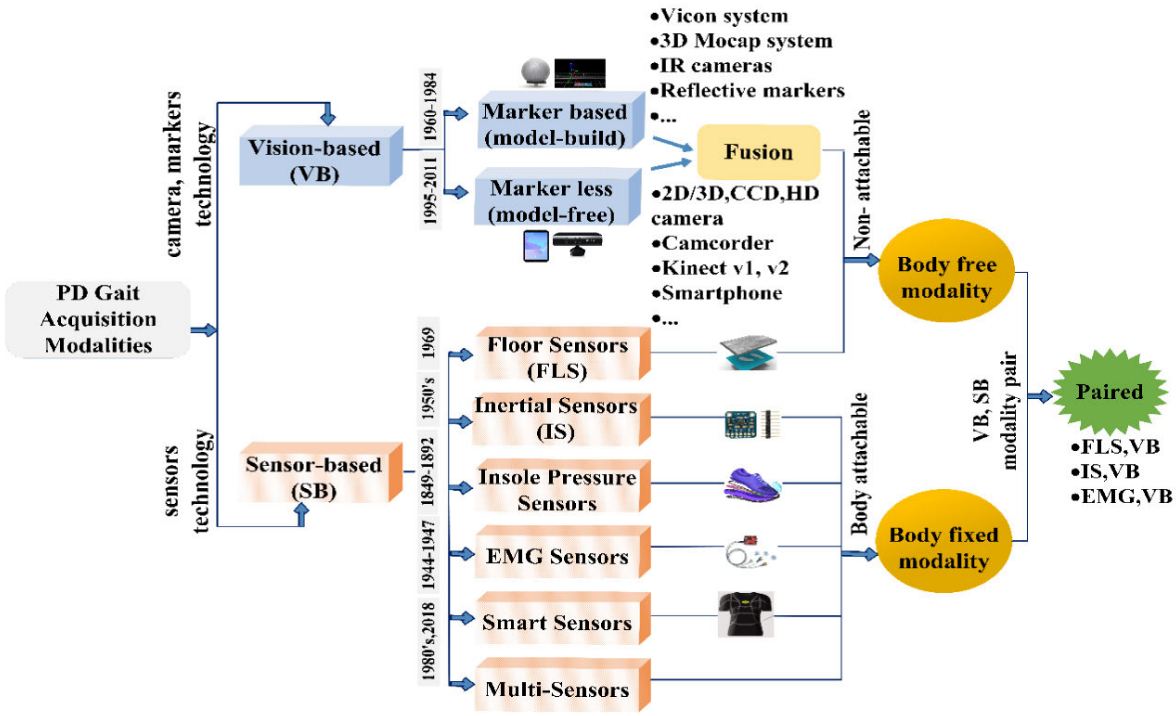


FIGURE 5. The proposed taxonomy of Gait Acquisition Modalities for PD diagnosis.

the gait features of 16 PD subjects and 16 normal controls using marker-less gait capture technology. Silhouette images were obtained by means of a high-quality video camera. An accuracy of 99.6995% was achieved using hidden Markov model (HMM) for PD detection. Similarly, in another study by Chen *et al.* [50], silhouette features from acquired videos using camcorder (VPC-HD1010) were extracted using LDA and outcomes obtained shown significant correlation with clinical scores with r = 0.92 (for testing) and 0.85 (for training).

Besides the use of video camera for gait acquisition for PD inquiry, many authors concentrated towards the tremendous applications of Kinect sensors, developed by Microsoft (MS). Kinect is a Mocap device that allows extracting detailed information of a subject's movement using the assimilation of color and an IR depth sensor leading to more accurate estimations and calculations. Prochazka *et al.* [15] made an effort to classify healthy and PD individuals using MS Kinect sensor. Spatiotemporal gait features of subjects were estimated by analyzing the skeleton joint structure derived through the Kinect. The use of Bayesian classification successfully yielded an accuracy of 94.1% for PD identification. Moving on the way to Kinect sensor for vision-based gait capture, another by Dranca *et al.* [52] proposed to develop a Kinect based system to compare and differentiate the severity levels of 30 PD affected patients. They applied two Kinect sensors to acquire PD gait with a sampling rate of 30fps and about 115 related features were determined. The Bayesian network then best predicted PD stages giving an accuracy rate of about 93.40%.

Apart from video cameras and the Kinect system, smartphone technology has given a new insight towards this field. The use of such technology can be analyzed in a study by Zhu *et al.* [53]. They tried to investigate the stride length parameter of PD patients using a mobile phone camera with a sampling rate of 30 fps. Results highlighted the potential of the applied system with an absolute error of 0.62 cm.

c: MB AND ML FUSION

However, both the vision-based modalities i.e. MB and ML offered high reliability for PD investigation, some of the research studies used the fusion of them (e.g. 3D Mocap system+ reflective markers and MS Kinect). In this category, Mocap systems in combination with markers were used as a 'gold standard' to compare the simultaneously captured results using Kinect, to check its efficacy in PD assessment. Eltoukhy *et al.* [13] presented a study to scrutinize and compare the gait variables of older adults suffering from PD and having no such disease. The gait data was gathered using Kinect v2, a Mocap system (BTS) and reflective markers concurrently. The study results demonstrated the correlation among both the systems, reflecting the potential of Kinect v2.

Another work reported by Galna *et al.* [54] tried to explore the capability of Kinect in diagnosing the movement of 9 PD and 10 healthy subjects. The experiment was conducted by initially collecting the gait data using 3D Vicon system along with markers as a benchmark and a Kinect system. Comparison among computed gait variables via both modalities manifested high correlation (r>0.8) proving the reliability of the Kinect sensor for PD inspection.

2) SENSOR-BASED (SB)

Besides VB modality, another way to acquire PD gait is through the use of sensor modality (SB). This section gives a brief overview of sensor-based modality for PD gait collection. This type of modality makes use of sensors which are either placed on the ground, known as non-wearable/ body free (e.g. floor sensors) or can be attached to the body of a person i.e. wearable/ body fixed (e.g. inertial, insole, EMG, smart sensors, etc.) as shown in Fig.5. Sensors when used, senses, records the motion (gait) of an individual and responds using the electrical signals. Depending on the captured PD gait signals, various biomechanical gait features can be estimated. Floor sensors (Kistler group, 1969) [43], [55] such as force plates are the sensors having potential to measure the ground reaction forces (GRF's) directly when the foot of the subject strikes on the floor. The forces thus obtained are then converted into an electrical impulse to extract relevant PD gait features [56], [57]. Another sensors i.e. Inertial sensors (Robbert Goddard, 1950's) [58], [59] are the devices employed on subject's body to perform linear acceleration, angular velocity and magnetic forces calculation easily using the ideas of inertia [60], [61]. Insole pressure sensors (Gaston Carlet, 1849-1892) [55] are the small devices embedded within the sole of shoes and captures the load/pressure during walking by the normal and PD subject [62], [63]. Similarly, EMG sensors (Venn Inman and colleagues, 1944-1947) [58] played a vital role in measuring muscle electrical actions of subjects in the form of EMG signals known as Electromyographs [64]. Finally, Smart sensors (Tesla, PrioVR, UK uni. etc., 1980's and 2018) [65], [66] visualized from Fig.5. such as smart clothes/garments were used by allowing the subject to wear it on their body to enable recording of entire body movements for PD gait acquisition [67].

In spite of having the huge capability of sensors technology to perform direct measurements of PD gait, it suffers from certain drawbacks such as the requirement of high cost, time, power and technical skills, wearing discomfort, drifting effect problem etc.[3], [12], [13], [48]. Thus, in this survey article, further SB modality is not explored and reviewed in detail.

3) PAIRED

The acquisition of PD gait by twining two classes of modalities such as inertial sensors, EMG sensors, etc. with a vision-based modality at the same time provides a more extended view for PD analysis and also saves data collection time than considering a single modality at a time. This category includes those articles that captured the gait of PD subjects using both vision and sensor modalities simultaneously to check the reliability of one against another (taking one modality as a gold standard). Several studies followed this pattern for PD gait inspection summarized in Table 3. Stack *et al.* [68] proposed to check the validity of wearable sensors in comparison to a VB system for detection of instability considering 24 subjects with and without PD problem. The study used five inertial measurement units (IMU's), an HD video camera mounted on a tripod to record different movements concurrently. Results achieved using inertial sensor (85% stable, 46% unstable) and video camera (70% stable, 30% unstable) demonstrated considerable correlation among both modalities. Kluge *et al.* [35] also presented a study with the aim to evaluate the concurrent validity and reliability of test-retest using a SB system (IMU's) against a Mocap camera-based setup as reference. Spatiotemporal and silhouette gait features were evaluated for the subjects and results shown good aggregation between the considered systems (r>0.95).

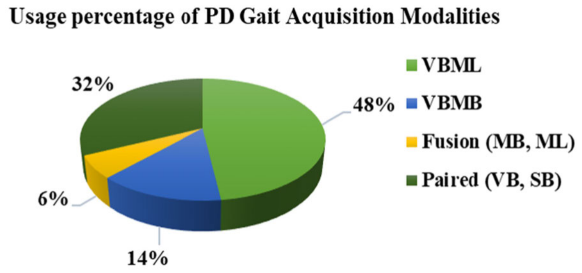


FIGURE 6. The Pie chart depicting the result of literature from (2005-2019) for usage ratio of various PD gait capturing modalities.

The use of sensors and VB modality simultaneously to collect PD gait was illustrated in another work by Eltoukhy *et al.* [117]. Using the combination of two force plates and a synchronized Kinect v2 sensor, they tried to determine GRF's from the gait of 9 PD patients. Outcomes revealed the high potential of Kinect in PD evaluation.

Table 3 gives the description of work that extensively focused vision-based modality for PD assessment emphasizing their relative benefits (+) and drawbacks (−). Approximately 71 related research articles are found out of which 48 studies have focused on using solo VB modality (10 on marker-based, 35 on markerless and rest on the fusion of both) and 23 studies compared both vision and sensor modalities simultaneously. The percentage usage of each modality is represented in Fig.6. Data analysis reveals most of the research related to VBML modality focusing Microsoft Kinect sensor due to its greater capability of capturing minute and depth details of the subject using image and depth sensors. Such unique features of Kinect can be useful for reducing freezing of gait (FOG) events in PD and more effective rehabilitation. No doubt, VB modality using optoelectronic system (markers and Mocap system such as Vicon) attains remarkable performance without any need of sensor but involve some flaws like the necessity of well-specialized laboratories and calibrated systems, high technical proficiency, large time requirements, etc. Further, sensor-based modality suffers from certain drawbacks that make it unsuitable for rich PD diagnostic purposes. VB marker less modality, on the other hand, provides an additional path to overcome the bottlenecks of marker-based modality as it is cost-effectiveness, simple to practice and virtually pervasive [3], [15], [51].

Therefore, from the literature survey of obtained articles on PD gait acquisition modalities, it is concluded that the exceptional features of VBML modality gained huge focus (about 50%) towards it as compared to other modalities for more profitable and effective analysis of PD in early stages.

B. DATA PRE-PROCESSING

Once the gait acquisition task is accomplished, another crucial step in a diagnostic process namely preprocessing is performed. In most cases, the data acquired via modality is not directly processed within the application, instead, it is preprocessed to enhance the data according to a specific task. Preprocessing involves the set of algorithms used to upgrade the quality of data by performing certain operations on it such as resizing, cropping, noise reduction, contrast adjustment, segmentation, etc. Thus, the intelligent preprocessing at the initial stages can lead to better results in the later stages. This section provides a brief overview of some gait data preprocessing techniques used by researchers in recent years to convert raw data into a suitable form for more effective PD diagnosis. Generally, there are two preprocessing methods that have been frequent applied i.e. filtering and object segmentation to provide improved PD analysis.

1) FILTERING

When data is acquired there are greater chances of it to get distorted due to the presence of some unwanted components such as noise, outliers, etc. Thus, filtering is a significant preprocessing step that provides refined and relevant data by means of some filters. Over time, several algorithms have been applied to reduce the effect of different kind of noise and errors to enhance the overall performance of the PD diagnostic system.

The use of a low pass filter can be seen in the study [69] to eliminate the random noise from PD gait data. A low pass filter basically compares the frequency of signals with the cut-off frequency and only encompasses those signals whose frequency is less than the cut-off frequency. This type of filter removes the high-frequency components and smoothens the data thus enhancing the quality. Under low pass filter, Butterworth filter (BF) is the frequently used filter and have the unique property of flat frequency response in the passband area [70], [71]. BW filter resolves the problem of blurred edges which is often encountered in an ideal low pass filter. Mathematically, the amplitude response of these filters can be given as

$$|G(k\omega)| = \frac{1}{\sqrt{1 + \left(\frac{\omega}{\omega_{cf}}\right)^{2n}}} \tag{1}$$

where ω_{cf} represents the cut-off frequency and n denotes the order of the filter.

BF can be of different order depending upon the roll-rate. A first-order BF [72] comprises of the roll-rate of 20dB/decade. As the order (n) increases, roll-rate grows simultaneously. The roll-rates of second-order and fourth-order BF are of 40db/decade and 80db/decade and increases for other higher orders. Also, the combination of Butterworth filters can be formed to create the one with higher-order but sometimes it results in declined performance due to the larger size. Another type of low pass filter named as Savitzky-Golay filter (SGF) [44], [51] has been adopted for smoothing of noisy data and is specifically preferred in biomedical applications. These filters are based on the idea of convolution and suppress the least square error that occurs while a polynomial is fitted at every frame of noisy data. Consider the dataset having $n\{u_i, v_i\}$ data points where $(i = 1,2\ldots n)$ and u, v_i are the independent and observation values. Then these can be represented as the set of p convolutional coefficient (D_i) as defined under

$$V_i = \sum_{j=\frac{1-p}{2}}^{\frac{p-1}{2}} D_i v_{i+j}, \quad \frac{p-1}{2} \leq i \leq n - \frac{p-1}{2} \tag{2}$$

Besides the low pass filter, the median filter [69] has been also practiced by the researchers to reduce the effect of salt and pepper noise from the gait data. These filters process the frame pixel-wise and swap each value with the neighboring pixel center. The key feature of median filters is its high potential in eliminating the noise without blurring the object as well as preserving the essential details of the data. In addition, Gaussians filters [34], [53], [73] have been applied to intensely remove the Gaussian noise from data. These filters make use of kernel having a standard deviation as a single parameter. Mathematically, Gaussian function in one dimension can be defined as

$$G_s(V) = \frac{1}{\sqrt{2\pi\sigma_{SD}^2}} e^{\frac{-V^2}{2\sigma_{SD}^2}} \tag{3}$$

Here, the assumed mean of the distribution is zero and σ_{SD} implies standard deviation. However, these filters are faster than the median filters but blur the edges while removing noise from the acquired data. Likewise, Woltring filter [54], [75] was used to smoothen the gait data collected from PD and normal subjects. This type of filter comes within the Vicon software and can refine the data with more ease.

2) OBJECT SEGMENTATION

The refinement of gait frames extracted from the videos is followed by a major preprocessing step known as object segmentation. Segmentation plays a crucial role in computer vision-based application where the purpose is to extract only an interesting region from the images. The filtered frames thus obtained from the previous step acts as input to this phase. Generally, in gait videos, the background scene is of no worth therefore background subtraction is performed to separate the foreground from background and make the data more suitable for relevant features extraction. In present times, the idea of background subtraction has gained huge popularity in the detection of objects from videos captured using cameras. There is a number of methods such as adaptive density estimation [3], bottom-up cues [49], thresholding (pixel intensity, color segmentation), etc. [16], [53], [69] designed and used by researchers to perform background subtraction of PD data and other applications.

Verlekar *et al.* [3] adopted the concept of adaptive density estimation method which involves kernel estimation to perform background subtraction. The resultant silhouettes were then extracted from 2D video using such a technique for further processing. The system achieved an accuracy of 98.8% in classifying PD and healthy subjects. In addition, a study by Shaw [49] used a bottom-up cues method to split foreground and background. The applied method proved to be more efficient as there is no requirement of and background learning model and past video frames. Then the quality of extracted silhouette images was enhanced using morphological erosion. Likewise, Alcock and Carlos [74] segmented human gait sequence using color-based and $\Sigma - \Delta$ estimation background subtraction methods. Color segmentation determines the differences between background and foreground and separates them on the basis of color distribution. It can be presented mathematically as

$$C_p(u,v) = \begin{cases} 1 & \text{if } d\left(I_p(u,v),\, N_p(u,v)\right) > T_{u,v,p} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where $I_p(u,v)$ denotes the frame pixel at time p, N_p (u,v) implies the established model up to p time, $d(I_p, N_p)$ is the function to provide differences between current frame and model, $T_{u,v,p}$ specifies each frame band and C_p (u,v) is the binary image having intensity of 1 for foreground and 0 for background. $\Sigma - \Delta$ operator method, on the other hand, updates a background tracker using a simple rule in which I_p (u,v) and N_p (u,v) are compared to increase or decrease Δ.

Segmentation of foreground and background pixels of gait frames using each frame's pixel brightness to extract silhouette images was performed by Khan *et al.* [16]. Initially, each frame of the video is converted from RGB to HSI color space. Then both the pixels are segmented using a brightness threshold and can be given as

$$\left\{ \begin{array}{ll} imv[x,y] = 1 & \text{if } imv[x,y] \geq \theta_{bt}(S_a, I_n) \\ imv[x,y] = 0 & \text{if } imv[x,y] < \theta_{bt}(S_a, I_n) \end{array} \right\} \tag{5}$$

where x and y are the pixel resolution of each video frame, S_a and I_n denotes the saturation and intensity threshold values for image $imv[x,y]$. The pixel values representing background are eliminated keeping that of the foreground.

Similarly, Lee *et al.* [69] used threshold technique and successively applied the region growing algorithm to attain the optimal results of segmentation. Another work by Chen *et al.* [76] proposed to remove the invariant background from collected gait videos of normal and PD subjects. Initially, the background image was built using each pixel's median intensity value as

$$A(u,v) = median_{TO}(I_{tm}(u,v)) \tag{6}$$

where I_{tm} (u,v) represents the brightness of the image at time tm and location (u,v). Here, $\mathrm{A}(u,v)$ is the value of background pixel and TO denotes the number of images present in the whole sequence. Afterward, the difference method was used to determine silhouette pixel of the subject's gait which can be defined as

$$F_{tm}(u,v) = 1 - \frac{2^* \sqrt{(\mathrm{I}_{tm}(u,v)+1)\,(\mathrm{A}(u,v)+1)}}{(\mathrm{I}_{tm}(u,v)+1)(\mathrm{A}(u,v)+1)} * \frac{2^* \sqrt{(256-\mathrm{I}_{tm}(u,v))\,(256-\mathrm{A}(u,v))}}{(256-\mathrm{I}_{tm}(u,v)) + (256-\mathrm{A}(u,v))} \tag{7}$$

$$\text{where} \quad \left\{ \begin{array}{ll} \mathrm{F}_{tm}(u,v) = 1, & \text{if } \mathrm{F}_{tm}(u,v) > THD \\ \mathrm{F}_{tm}(u,v) = 0, & \text{otherwise} \end{array} \right\} \tag{8}$$

$$\text{And} \quad THD = \frac{1}{P} \sum \frac{\mathrm{A}(u,v)}{256} \tag{9}$$

Here, P denotes all the pixels in the constructed background image, THD is the threshold ranging from [0 to 1] on the basis of which foreground and background pixel separation are performed.

Finally, on the completion of background segmentation, normalization is performed to make the system more efficient and vigorous to scale changes. The use of the Butterworth filter is mostly adopted due to its wider applications in motion analysis. Also, thresholding background segmentation seems to be easy to use and chiefly employed for PD diagnostic purpose. Thus, preprocessing is necessary to make the data more valuable that can be efficiently used for quality PD assessment.

C. FEATURE EXTRACTION

Once the gait data have been fully preprocessed, related features are detected which then serve as input to the third stage of PD detection pipeline i.e. feature extraction. This step transforms the pictorial data into a quantitative representation that can be easily used for further processing. In PD, a different type of gait features of the normal and affected subjects can be extracted to perform the diagnosis such as knee flexion, adduction, abduction, joint angles, etc. Since the extraction of a large number of features take huge time and reduces the accuracy too, therefore, feature selection is performed. The prime goal of feature selection is to reduce the dimensionality of feature set by selecting a subset of best-optimized gait features that can better represent the input data and still achieve high accuracy rates. In PD diagnosis, several methods have been used to perform extraction and selection including PCA [48], [77], LDA [50], [78], FFT [71], KFD [79], wrappers etc. The detailed explanation of each is provided in Section 4.

D. CLASSIFICATION AND RESULT

The basic purpose of the classification is to differentiate the objects based on some attributes. In PD recognition, a classifier is applied to categorize the subjects into different classes (normal/ abnormal) on the basis of their gait features. In recent years, PD identification has been performed by means of different machine learning techniques such as supervised (SVM, ANN, KNN, etc.) [75], [80], [81], unsupervised (K-means, etc.) [14], [82], distance-based, probabilistic [49] etc. The elaborated description of these methods has been presented in Section 5.

IV. GAIT FEATURES AND EXTRACTION/SELECTION METHODS FOR PD ANALYSIS

A. PD GAIT FEATURES

A feature defines the unique property of an individual based on which it is possible to distinguish normal and pathological behavior. Gait acquisition modalities (as discussed in Section 3) capture such prominent attributes which are useful in PD investigation. This section presents a description of frequently recorded gait features considered for PD analysis shown in Fig. 7 and are classified into the following categories:

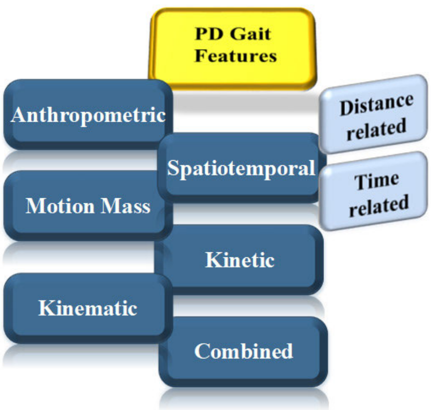


FIGURE 7. Most commonly used gait features for PD analysis.

1) ANTHROPOMETRIC FEATURES

These are the basic demographic features that impart fundamental details of the subject such as age, height, weight, gender, limb length, etc. Most of the PD studies have considered PD and healthy subjects only with identical anthropometric data to determine their effect on an individual's gait for more reliable PD identification [82], [83].

2) SPATIOTEMPORAL FEATURES

Analyzing the phases of the gait cycle provide some basic measures i.e. Spatiotemporal which are associated with distance (spatial) and time (temporal). Spatial gait features involve stride and step length, step width, etc. whereas temporal features are concerned with timing events in the gait cycle such as cadence, swing and stance period, single-limb support time, double support time, etc. [84]. The range of differences among such parameters (e.g. cadence value for young, adult, elderly age are: 172-144, 113-118 and 58-70) [85] significantly indicates the presence of PD in an individual. Aich *et al.* [82] proposed a study to compare the gait features obtained via wearable and a 3D Mocap system for freezing of gait (FOG) assessment in PD. Five spatiotemporal gait features i.e. step time, stride time, step length, stride length and walking speed were estimated using initial contact (IC) events and calculated using the equations:

$$Step\ Time\,(v) = IC(v+1) - IC(v) \tag{10}$$

$$Stride\ Time\,(v) = IC(v+2) - IC(v) \tag{11}$$

where v is the IC events index. To calculate step length, an extension of the inverted pendulum model was used as

$$Step\ length(S_l) = M_G^{*}2\sqrt{(2N_pC - C^2)} \tag{12}$$

$$Stride\ length(S_r) = 2^{*}Steplength \tag{13}$$

where N_p is the sensor height w.r.t ground and C represents a change in the height, M_G acts as multiplier factor for position mapping of the accelerometer to pendulum model's center of mass and

$$Walking\ speed\ (W_s) = \frac{Mean\ S_l}{Mean\ S_r} \tag{14}$$

The results obtained using support vector machines (SVM) provided 80% accuracy and less than 10% mean error rate between the two systems showing the effectiveness of wearable sensors for prediction of FOG. In another study by Shaw [49] considered gait image sequences to detect patients with PD using hidden Markov model (HMM). Initially, the silhouette was extracted from the input video frames and a boundary box was built enclosing the subject's silhouette for measuring a number of spatiotemporal gait features such as cadence, step length, stride length, height, width, gait cycle length. Study outcomes showed the potential of the proposed model for PD diagnosis.

a: ENHANCED SPETIOTEMPORAL FEATURES

Traditional spatiotemporal features consider gait in the form of templates sequence whose space and computational time complexity is very large. To tackle this problem, Ortells *et al.* [12] used an improved spatiotemporal feature to study i.e. Gait Energy Image (GEI) to study gait and postural features of normal and PD subjects. In spite of directly considering raw silhouette, the mean image obtained by normalization of binary silhouette sequence was utilized to provide robustness to silhouette flaws. Simply, GEI can be defined as

$$G_E\,(u, v) = \frac{1}{P}\sum_{s=1}^{P} I_o(u, v, s) \tag{15}$$

where P denotes the total number of silhouette frames in the gait cycle, s is the frame number at an instant and $I_o(u,v)$ indicates original silhouette image with (u,v) values in 3D coordinate. Two GEI representations were made from entire silhouette sequence, a sample oh which is shown in Fig.8.

Once GEI's are constructed, other gait features (e.g. asymmetry in stance, swing phase, step length, intensity, amplitude, falling risk) were calculated. Results demonstrated the relevance of GEI in the evaluation of PD gait.

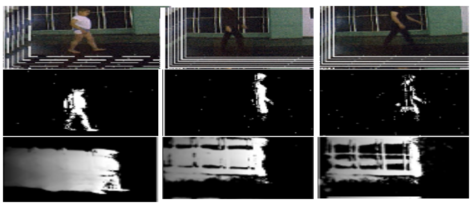
In alternate to GEI, a simple motion history image descriptor (MHI) was adopted by Alcazar *et al.* [86] for classification

FIGURE 8. A representation of extracted GEI from the entire sequence of silhouette gait from the study [12].

of normal, musculoskeletal and PD gait using marker-less strategy. On extraction of silhouette from acquired video frames, MHI video descriptor is constructed that represents human gait dynamics and entire silhouette sequence in a single image as shown in Fig.9. It can be defined as

$$M_T(u, v, s) = \begin{cases} T \ \text{ if } C(u, v, s) = 1 \\ -\max(0, M_T(u, v, s-1) - 1) \\ \text{otherwise} \end{cases} \tag{16}$$

Here, $M_T(u,v,s)$ denotes MHI, $C(u,v,s)$ represents changes in segmented silhouette and T is the sagittal gait period. The sensitivity of 80% has shown the robustness of the used approach in clinical PD investigation.



(a) (b) (c)

FIGURE 9. A depiction of motion history images (MHI) (bottom row) extracted for (a) normal (b) musculoskeletal and (c) PD gait used in the study [86].

3) KINEMATIC FEATURES

Kinematic features are simply related to the human body joints motion and are captured using an optoelectronic system (camera and markers). The markers are fixed to the subject's body anatomical landmarks of interest. Such type of features such as joint angles, acceleration, velocity, joint position, displacement, range of motion (ROM), motion route, etc. provides a more convenient way to analyze PD affected gait [25], [85]. Jovicic et al. [87] presented a study to classify PD and healthy subjects based on kinematic data captured using the inertial sensor and a video camera. Foot rotations, flexion angles were measured and the neural network was applied to differentiate the subject's walking patterns. Results showed the effectiveness of sensors in PD FOG detection giving 16% error between both the systems.

In the Kinect sensor, landmark locations on the subject's skeleton model help in more accurate measurement of kinematic gait features. A study proposed by Galna *et al.* [54] made an effort to compare the capability of Kinect sensor against a Vicon gold standard for PD analysis. Kinematic features including ROM, trunk, hip and shoulder flexion's, virtual displacement of the wrist, etc. were determined for 9 PD and 10 healthy subjects. Statistical evaluation measures demonstrated high correlation between both the systems (r>0.8).

4) KINETIC FEATURES

Kinetic features deal with the study of two most frequently used variables i.e. forces and moments which are produced during walking. Force platforms and another kind of sensors (e.g. EMG, IS, etc.) are employed to capture such data. When these sensors are worn on the body or when the foot strikes the ground, GRF's and other data is directly measured for further computations. Also, time domain or statistical (root mean square: RMS, mean, standard deviation, kurtosis, Skewness, etc.) and frequency domain (mean and median frequency, power spectrum, etc.) features can be extracted using sensor data to analyze the FOG and turning episodes (turn time, no. of turns, freezing index, etc.) in people suffering from PD for more accurate diagnosis.

Mezzarobba *et al.* [88] proposed a study to analyze FOG events in order to classify PD subjects from normal. Using kinetic and kinematic data (center of mass: COM, the center of pressure: COP). The analysis revealed more postural deflects in PD with FOG subjects as compared to others and high relevance of COP than COP in PD inspection. Another study by Bailey *et al.* [70] explored frequency and time domain features (RMS, modulation index, covariance, asymmetry index, etc.) to test the reliability of PT-RAS therapy in reducing asymmetry in PD patients. Statistical analysis of considered gait features shown proficiency of the therapy in decreasing gait asymmetry in PD ($p<0.05$) from 23 to 36%.

5) MOTION MASS FEATURES

However, the aforementioned PD gait features provide useful information about body motion but don't indicate smoothness of the motion. Thus, motion mass features provide a set of features that describes the amount and smoothness of the motion [14], [89]. Consider Z as the set of all joints of the body where each point z_i demonstrates one body joint and p as the joints of interest i.e.

$$Z = \{z_1, z_2 \ldots . z_p\} \tag{17}$$

With each body joint z_i three variables are associated such as Eucledian distance (E_z : summation of distances computed between start and ending location for a given body joint E_{z_i}), acceleration mass (A_z : total of accelerations at each instant of time for every joint A_{z_i}) and trajectory mass (T_z : trajectories length summation for joints of interest at given time instantb T_{z_i}) represented as

$$V_z = \sum_{i=1}^{p} V_{z_i} \tag{18}$$

$$A_z = \sum_{i=1}^{p} A_{z_i} \tag{19}$$

$$T_z = \sum_{i=1}^{p} T_{z_i} \tag{20}$$

These parameters can be defined in the form of a single vector as

$$MM_{z_i} = \{E_z, A_z, T_z, t_m\} \tag{21}$$

where t_m denotes movement's time length. A study by Krajushkina et al. [90] successfully classified PD and healthy subjects using motion mass features collected via Kinect sensor system. Similarly, Nomm *et al.* [14] presented a study to monitor gait deviations among PD individuals and healthy controls based on motion mass parameters. They extended the original motion mass features (defined above) by three additional features i.e. velocity mass (V_z : *a* total of velocities at each instant of time) similar to acceleration mass, trajectory ratio (trajectory mass and combined eucledian distance ratio) and acceleration ratio (acceleration mass and combined eucledian distance ratio) as

$$V_z = \sum_{i=1}^{p} V_{z_i} \tag{22}$$

The proposed study efficiently classified such gait features for both the groups that can be useful in PD investigations.

6) COMBINED

For more valid PD inspection, several efforts have been made to pool information from multiple gait features to enable broader visualization of deviations among gait patterns. A computer vision approach was developed by Chen *et al.* [76] for gait analysis of 24 PD and healthy subjects. The combination of spatiotemporal (gait cycle period, stride time, walking velocity, cadence) and time-frequency domain (power spectrum) features was extracted from the binary silhouette of subjects. The proposed approach attained an accuracy rate of 80.51% using minimum distance classifier. In another work, given by Prochazka *et al.* [15] used the amalgamation of spatiotemporal (average stride length, speed) and kinematic (joint angles) gait features to inspect the gait differences among PD and normal subjects. Depth information was captured via Kinect sensor and an accuracy of 94.1% has been achieved.

The comparison among spatiotemporal, kinematic and kinetic gait features was made by Svehlik *et al.* [92] for PD analysis. This fusion of gait parameters was acquired using 12 camera Mocap system, reflective markers and four force plates. Results indicated small stride length, large double support periods, less range of joints motion and reduced power generation in PD as compared to healthy controls.

B. PD GAIT FEATURE EXTRACTION/SELECTION METHODS

As dimensionality of data grows, it adversely deteriorates the performance of the learning model. The curse of dimensionality results in increased computational cost, algorithm complexity, and overfitting issue. To address these problems, two techniques namely feature extraction and feature selection are mostly preferred. A number of such techniques exist and this section inclusively focuses those that have been used for the purpose of extraction and selection of Parkinson's gait features based on taxonomy shown in Fig. 10 and presented in Table 4. Feature extraction is an essential process to extract relevant attributes from the segmented objects. At time s, a large number of features extracted lead to unnecessary classification errors. Thus, feature selection is applied whose overall purpose is to transform large dataset into a smaller one that retains original data and provides sufficient information. Following methods have been employed for detection of relevant PD gait features over irrelevant ones:

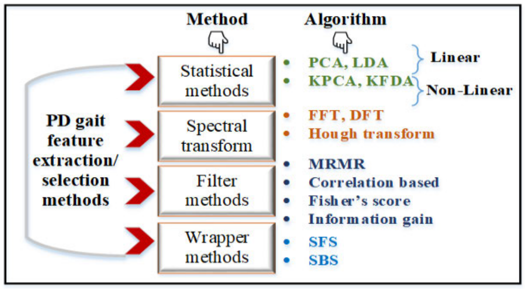


FIGURE 10. Feature extraction/ selection methods frequently adopted for PD diagnosis.

1) STATISTICAL

These are the simplest and widely chosen PD feature extraction methods such as PCA, LDA, kernel-based PCA (KPCA), LDA (KFDA) that reduces the dimensionality of feature set capably. Principle component analysis (PCA) [77], [82], [83], [93], a linear method assumes direct relation between variance of features and extent of information carried by that feature. It transforms feature set into low dimensional feature space by preserving the maximum variance in data. This conversion thus gives principle components P_c (eigenvalues) which simply represents original feature vectors linear combination as

$$P_c = b_{c1}y_1 + b_{c2}y_2 + \cdots + b_n y_{cn} \text{ where the value of} \sum_j b_{cj}^2 = 1 \tag{23}$$

In order to guarantee the usefulness of class discrimination, Linear/Fischer discriminant analysis (LDA/FDA) [50], [78], [94] is used that maximizes the data classification (increase intercluster distances and reduce intracluster distances) based on the idea of separating two classes by finding the linear combination of variables. Another method such as KPCA [76], an extension of PCA is based on a kernel that performs non-linear mapping to reduce the dimensionality of the feature set and decreases the computational complexity to a greater extent. This method initially maps the input data into a feature space using non-linear mapping and then applies linear PCA on that feature space. Similarly, KFDA [79], an extended version of LDA works on the same principle and

TABLE 4. Shows the summary of considered PD related gait features, extraction/selection methods along with the gait sensing resource and accuracy rates.

Author/ Year	Resource	Gait features	Feature ext./selc method	Participants	Performance	Conclusion
Aich et al. [77]/ 2018	• 3D Mocap system	• Spatiotemporal: SPT(stride length, foot clearance)	• MRMR • FS • SFS • PCA	20 PD, 20 HC	• 98.54% (SVM coupled with MRMR)	MRMR method had the high potential to remove redundant data and provides quick response for early diagnosis of PD
Dranca et al. [52]/ 2018	• 2 Kinect sensors	• Kinematic (joint positions, angles)	• CBFS • IG	30 PD	93.40% (Bayesian class.)	Kinect sensor and selected feature selection method provided inexpensive diagnosis of PD stages as well as FOG
Mezzarobba et al. [88]/ 2018	• 7 camera Mocap system • 2 force plates • 24 reflective markers	• Kinematic and kinetic (COP, COM)	• PCA • LDA	24 PD,12 HC	• p< 0.001 (COP trajectories) • p< 0.01 (COP positions)	PD with FOG shown more postural defects and different COP trajectories than PD with non FOG and healthy subjects
Pissadaki et al. [71]/ 2018	• 2 inertial sensor devices • Kinect v2	• Spatiotemporal, kinetic, kinematic	• FFT	60 subjects (33 F,27 M)	-	The proposed system proved to be useful for daily activity monitoring in PD patients
Aich et al. [82]/ 2018	• 9 IR cameras • 3D Vicon system • 2 accelerometers	• Spatiotemporal (step and stride length, step and stride time, speed)	• PCA	51 PD	• 88% • mean error rate < 10%	The high correlation between both the systems shown their applicability in real life scenarios for PD assessment
Krajuskina et al. [90]/ 2018	• Kinect sensor	• Motion mass (trajectory and acceleration mass, combined eucledian	• FS	20 PD, 20 HC	0.75-0.85 (accuracy range)	Consideration of test's time duration didn't enhance the quality of the model
Verlekar et al. [94]/ 2018	• RGB-D (Kinect) camera	• Kinematic and spatiotemporal	• LDA	Neurological and normal subjects	95%	The proposed system using VGG-19 CNN outperformed existing systems for PD gait classification
Hidalgo et al. [93]/ 2017	• A smartphone camera	• Kinematic and spatiotemporal (GEI)	• PCA	5 gait (HP, DP, NP, PD, normal)	74%-80%	Results demonstrated the suitability of smartphone in capturing PD data and more robust analysis
Spasojevic et al. [78]/ 2015	• Kinect sensor	• Spatiotemporal (gait speed, symmetry ratio) and kinematic (joint angles, ROM, angular velocity)	• LDA	12 PD	70%-90%	Use of low cost Kinect sensor can be effective for home based analysis of subjects with PD
Wahid et al. [79]/ 2015	• 8 camera Vicon system • 15 reflective markers • 2 force plates	• Spatiotemporal (stride and step length, double support time, speed, etc.)	• KFDA	23 PD, 26 HC	92.6 % (highest with RF using multiple regression)	The proposed multiple regression based normalization model proved to be useful in PD rehabilitation using SPT gait features
Dillmann et al. [104]/ 2014	• 3D real time Mocap system • Reflective markers	• Spatiotemporal (speed, cadence, velocity)	• PCA	36 PD, 35 HC	p< 0.001	PD subjects walked with less speed, velocity than normal and can be used as important measures in PD inspection.
Yin et al. [50]/ 2012	• A camcorder (VPC- HD1010)	• Spatiotemporal	• FFT • LDA • PCA	12 PD	r= 0.92 and 0.85 (for training,	Developed regression model system seemed to br more reliable for evaluating abnormality in PD

TABLE 4. *(Continued.)* **Shows the summary of considered PD related gait features, extraction/selection methods along with the gait sensing resource and accuracy rates.**

Chen et al. [76]/ 2011	• A digital CCD video camera	• Time- frequency (spectral power, freq. signals) and spatiotemporal features (gait cycle	• KPCA • DFT	12 PD, 12 HC	80.51%	Results indicated the feasibility of KPCA method in evaluating motor symptoms in PD patients
Cho et al. [48]/ 2009	• A CCD camera	• Spatiotemporal and frequency domain (speed, energy, etc.)	• PCA • LDA	7 PD, 7HC	95.49%	LDA shown more accuracy than PCA and the proposed system revealed its efficiency in identifying PD gait
Lee et al. [69]/ 2008	• A high quality S-VHS video camera	• Kinematic(joint angles) and spatiotemporal (swing time distance)	• SBS • Hough transform	40 PD, 50 HC	76.1%-83.7%	Outcomes indicated the relevance of time swing distances in characterizing PD gait from normal ones.

provides a more reliable classification in dealing with non-linearly separable data.

2) SPECTRAL TRANSFORM

These are the mathematical models that transform the real signal into the frequency domain and then extract the frequency-related features. The methods like FFT, DFT, Hough transform have been used to achieve the feature extraction in PD analysis. Fast Fourier transform (FFT) [50], [71] is the fast computational algorithm for Discrete Fourier transform (DFT) [76] where both methods perform similar measurements on the input signal and produce exactly identical output. The array of time-domain waveform samples is processed using FFT/DFT that results in an array of frequency domain samples. Considering $y(n)$ and $Y(P)$ as time and frequency domain signals having length N, the time to frequency calculations can be given as

$$Y(P) = \sum_{n=0}^{N-1} y(n)e^{-j\frac{2\pi nP}{N}} \tag{24}$$

Another method known as Hough transform [69] has been used to extract the features from arbitrary or unknown shapes (lines, circle, ellipse, etc.) in a more efficient way. This method significantly performs well with improved speed and accuracy for feature extraction in computer vision-based applications.

3) FILTERS

These are the feature selection methods which extracts the data features based on their relevance and without relying on any type of learning model. In PD analysis, multivariate filters have been considered to determine the relation among features and perform computation efficiently. Minimum redundancy maximum relevance (MRMR) [77] filter method enhances the relevance and reduces redundancy in every class using mutual info and linear relation for both categorical and continuous variables and provides low error rates for the feature selection process. Correlation-based feature selection (CBFS) [52] method works on the concept of heuristic merit to minimize the cost of feature selection. CFS takes into account each feature individually, identifies their predictive value and amount of correlation. Similarly, Fisher's score (FS) [90] based filter method assumes assignment of identical values to similar class samples and vice-versa but these are not much capable in handling redundancy.

Another filter approach i.e. info gain (IG) [52] for the feature selection represents the amount of information revealed by the feature for the particular class and chooses features based on that information. Also, the Chi-square test provides another alternative way to select features from the entire dataset by calculating the differences between observed and expected frequencies in one or more classes. High speed and computational simplicity, however, make the filter methods more robust to use in feature selection but they can reduce the performance of classifier due to lack of interaction among classifier and the method used.

4) WRAPPERS

The capability to overcome feature independence issue is the unique feature of wrapper methods. In contrast to filter methods, these extracts the feature by taking learning model into a concern which acts as a black box. Wrapper methods make use of sequential search strategies (such as SFS, SBS) to find the best subset of the feature. Sequential forward search (SFS) [77] is the greedy search algorithm which initiates from an empty set, pick up the feature u^+ and adds it in the already selected feature X_K to maximize $j\,(X_{K,}u^+)$ but works well on a small optimal set of features. Sequential backward search (SBS) [69], on the other hand, functions reverse to the SFS as it begins from the entire set, removes the feature u^- that least minimizes the objective function value $j\,(X-u^-)$. The biggest drawback of this SBS is that it can't evaluate the feature again once discarded. Wrapper methods thus offer better accuracy estimates but are computationally very expensive and slow than filter methods.

Table 4 provides an overview of work on different feature extraction and selection methods including the type of modality used, extracted features and related accuracy rates for PD investigation. Based on number of articles obtained, amongst all the considered PD features the mixture of two or more features have been frequently adopted as it allows more extensive analysis of PD affected gait using number of features (e.g. joint moments, angles, rotation, forces, energy, gait cycle events, etc.) simultaneously for evaluation and can result in improved classification accuracy. Further, data analysis of obtained references reveals the use of statistical methods the most (about 52%) due to their simplicity and easy applicability as compared to other feature extraction/selection methods, especially focusing on PCA (24%) followed by LDA (approx.. 20%). The usage ratio of each is depicted in Fig. 11.

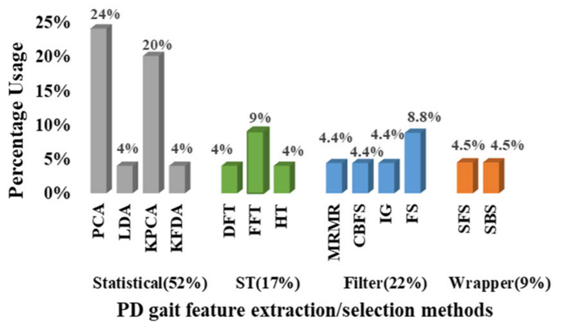


FIGURE 11. Plot showing the usage ratio (in %age) of feature extraction/selection methods used for PD analysis based on the literature from past 15 years.

The unique property of PCA to reduce the complicated feature set into a simpler and smaller dimension without any loss of details and being unaffected by outliers make it robust to extract relevant PD gait features and attracted most of the research towards it. Also, due to the decreased error rates feature, LDA has been preferred to attain maximum accuracy for PD analysis.

V. MACHINE LEARNING TECHNIQUES USED FOR PD RECOGNITION

In today's scenario of artificial intelligence (AI), the demand to handle data efficiently by making the machines more intelligent like a human is in the rise. The prime goal of machine learning (ML) is to provide direct interpretation and extraction of useful patterns from the processed data by designing algorithms that learn from experiences in labeled data form as

$$U = \left\{u^{(n)} \varepsilon M^d\right\}_{n=1}^{N}, \quad V = \left\{v^{(n)} \varepsilon M\right\}_{n=1}^{N} \tag{25}$$

Here U is the feature set where $u^{(n)} = [u_1^{(n)}, u_2^{(n)}, \ldots, u_d^{(n)}]^T$ is known as a feature vector and V represents label set. Prediction of output via MLT involves partitioning the data into three classes i.e. training (to train the model), validation (to calculate model's fit) and test (to estimate model's performance). This section discusses various ML algorithms used in recent years for PD diagnosis depicted in Fig. 12. Depending

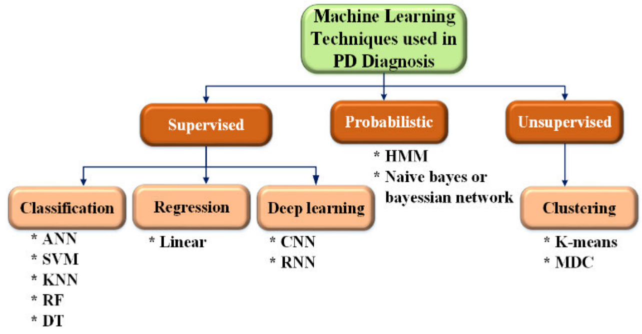


FIGURE 12. The hierarchy representing major machine learning techniques applied in PD detection.

upon the related data obtained, these techniques are categorized into supervised (classification oriented), unsupervised (clustering oriented) and probabilistic.

A. SUPERVISED LEARNING

The most common ML technique is supervised learning which requires an external supervisor to label the feature vectors. This learning tries to predict the function (from labeled data) that best represents the feature and label set relationship. Supervised learning reduces the risk of error occurrence and is used to tackle classification (if every feature vector y relates to the label z $\in$M, M = $\{J_1, J_2 \ldots J_c\}$ and regression (if every feature vector y relates to the real value z $\in R_v$) problems. This type of learning includes various classifier such as artificial neural networks (ANN), support vector machines (SVM), regression models, decision trees (DT), K-nearest neighbor (KNN), random forests (RF), deep learning (CNN, RNN), etc.

ANN is the rich paradigm to duplicate the biological functioning of neurons in the brain artificially. These type of networks are trained using a number of iterative algorithms including gradient and conjugate descent, Levenberg algo, back propagation algo, etc. and are implemented to resolve critical classification problems [71], [81]. In PD analysis, two variants of neural networks are often considered i.e. multi-layer perceptron (MLP) (having input, output and multiple hidden layers) [78] to deal with large, complex computations and radial basis function (RBF) [69] which is more intuitive than MLP and stores examples in training set in the form of prototype. A research work by Spasojevic *et al.* [78] performed the classification of normal and PD subjects using both MLP and RBF type neural networks. The gait data was captured using a Kinect device and the results obtained indicated the highest accuracy rate with ANN-MLP (approx. > 90%). Similarly, Lee *et al.* [69] utilized the combination of SBS and General Regression neural network (GRNN) in order to select the relevant gait features and to classify the PD and healthy controls. The proposed strategy yielded an accuracy rate of 88.4%. The architecture of GRNN is shown in Fig. 13.

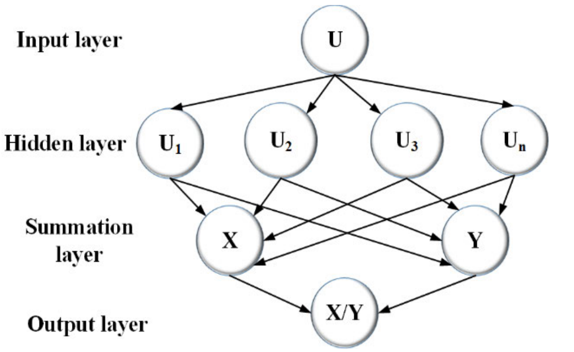


FIGURE 13. The proposed architecture of GRNN used in the study [69].

It consists of four layers- an input layer, hidden layer, summation layer and output layer. The variable U is passed to hidden layer (having every training sample i.e. $U_1, U_2, U_3, \ldots U_n$ through input layer. The square distance (D_{is}^2) between an unknown pattern (U) and training sample is then computed and passed to the kernel function. The units of summation layer- X performs minimization of exp $[-D_{is}^2/(2\sigma^2)]^*$ Y_i associated with U_i and Y performs the minimization of exp $[-D_{is}^2/(2\sigma^2)]$ which provides the output of the predicted result. Although, ANN has been popular due to its unique benefits but suffers from certain drawbacks such as hardware dependency, hard interpretation, etc.

SVM is another supervised learning platform which is based on the concept of the kernel to handle non-linear problems and uses hyperplane to distinguish classes in feature space as

$$f(y) = \sum_{j=1}^{n} w_j \phi_j(y) + b \tag{26}$$

where w_j is the weight of hyperplane, b denotes its bias and ϕ_j represents a non-linear function. The margin calculations thus provide the distance between classes that should be kept maximum to minimize the error of classification. Authors such as [86] used SVM to classify differences among PD and normal subject's gait. Nieto-Hidalgo and García-Chamizo [93] made an effort to classify five types of gait patterns including PD gait by applying SVM classifier. An important gait feature i.e. GEI was recorded using vision-based approach. Results demonstrated the reliability of SVM in pathological and normal gait analysis with different accuracy rates. Similarly, a study by Tahir and Manap [81] successfully analyzed the deviations among PD and healthy gait with an accuracy rate of 90.6% with ANN and 95.8% with SVM, revealing the potential of SVM in gait research. SVM, however, have great potential to deal with complex problems without causing overfitting but the selection of kernel serves as a hurdle in such classifiers.

DT [15], [80](a non-parametric classifier) is preferred to solve classification problems by designing a model that can determine the output via some decision rules. Internal nodes of the tree correspond to the test applied and the outcome is represented by tree branches. Prochazka *et al.* [15] proposed a study to investigate the gait differences among 18 subjects with PD, 18 normal and 15 young persons. The gait data acquisition was performed via MS Kinect. The comparison of gait for the considered subjects using DT classifier provided an accuracy of 94.1%. These classifiers are easy to understand and interpret but are unstable and can lead to overfitting issues. To handle such problems, a forest is created with the ensemble of decision trees known as random forest (RF) that can efficiently deal with high dimensional data [77], [95]. So these classifiers start with building decision trees and combines them to get improved and stable results without any need of tuning hyper-parameter.

Similarly, another approach in PD analysis includes KNN [52], [93] based on the concept of similarity among features to classify the data and doesn't require any prior details about the distribution of the data. Wahid *et al.* [79] tried to differentiate 23 PD and 26 healthy subjects based on Spatio-temporal gait features (stride length, step length, double support time). Five classifiers were used to evaluate the accuracy of proposed system, out of which KFD, SVM and KNN yielded good results. So, KNN has the capability to tackle noisy and irrelevant data but the selection of 'k' value is still a challenging task. Regression models [50], [96] (linear regression) have been also used by various researchers for predictive analysis to enable PD diagnosis. This classifier tends to determine the relationship between the dependent and independent variables using linear equations. A vision-based regression model was proposed was Chen *et al.* [50] to evaluate the gait deviations among PD and normal subjects using monocular image sequences. Overall motor abnormality (MA_n) was measured using a linear regression model. The foot movement abnormal index ($FMAI_n$) and posture abnormal index (PAI_n) were fitted for all the subjects as

$$MA_n = \beta_0 + \beta_1^* PAI_n + \beta_2^* FMAI_n \tag{27}$$

where β_0, β_1 and β_2 are constants calculated using the minimum sum of square residual procedure (MSRS). The outcomes demonstrated the correlation with UPDRS scale with $r = 0.95, 0.85$ for training, testing and $p < 0.0001$.

The need for human expertise to determine the applied features in order to decrease the data complexity often limits the performance of ML techniques. Therefore, an improved paradigm named as deep learning that runs through manifold abstraction levels in data has been designed to make updations in ANN. Deep learning techniques [94], [97] are the set of machine learning algorithms to deal potentially with the growing amount of data as more the volume of data, higher is the accuracy. The greater depth of the network automatically enhances the performance of the system. Convolutional neural network (CNN) and Recurrent neural network (RNN) is the forms of such learning techniques that have been applied to perform classification of video, images, text, etc. Sun *et al.* [98] determined FOG events in 45 PD patients by comparing the gait features of subjects using three deep learning techniques i.e. convolution 3D attention network (C3DAN), long-term RNN and spatiotemporal multiplier network (extension of Convnets).

The proposed system (C3DAN) outperformed other algorithms by achieving an accuracy of 79.3%, sensitivity equals to 68.25 and specificity of 80.8%.

B. UNSUPERVISED LEARNING

Unsupervised learning techniques eliminate the need of assumption to be made on the labels and the patterns are inferred within the dataset using a predefined metric. In PD analysis, clustering techniques such as minimum distance classifier [48], [76] (MDC), K- means [14], [95] which divides the data into clusters depending upon their likeness and disparity, have been focused to perform classification of gait deviations among PD affected and healthy controls. In k-means clustering, the grouping of feature vectors is performed on the basis of the relative distance between them (closer forms one group and vice-versa). This technique reduces

$$V(D) = \frac{1}{n}\sum_{j=1}^{n} e\left(y_j, D_i\right) \tag{28}$$

where $e(y_j, D_i)$ is the distance between clusters and D_i denotes the centroid/mean. Cho *et al.* [48] explored the reliability of a vision-based system to note the differences between PD and healthy (7 each) gait. MDC was utilized to check the accuracy of PCA and LDA in feature extraction. The study results revealed the high recognition rate with LDA than PCA indicating the potential of MDA in pathology detection. Again, Soltaninejad *et al.* [95] used k- means unsupervised learning for measurement of Time-Up and GO (TUG) data to classify PD and healthy groups. The proposed technique and k-means showed high performance in PD assessment. Thus, unsupervised machine learning techniques seem to be more effective for PD inspection but it is very problematic to define the learning objective.

1) PROBABILISTIC LEARNING

As the name suggests, this type of learning is based on the probability theory that represents uncertainty about models. Probabilistic learning has the potential to predict and provide probability distribution for the set of classes. Hidden Markov models (HMM), Naive Bayes (NB) or Bayesian networks are the main examples of this learning used in PD inquiry by [49], [77], [82]. The working of NB classifier is based on the conditional probability that builds trees on their occurrence probability and is used to solve classification as well as clustering problems. A study by Shaw [49] adopted HMM for classification and detection of PD gait by analyzing the sequences of postural images. The binary silhouette was preprocessed using morphological operations and the training of HMM was performed using Viterbi and Baum-Welch algorithms. The use of statistical measures and HMM thus provided an accuracy rate of 99.6995%. Another work by Aich *et al.* [77] proposed to classify PD patients with shuffling gait from older adults. The analysis of gait signals was performed using SVM, RF and NB. The results obtained from all the classifiers revealed the accuracy and reliability of proposed method to detect PD at early stages.

Table 5 highlights the mostly adopted machine learning techniques for PD identification with their respective pros (+) and limitations (−). The available data reveals about 81% of research towards supervised learning preferably focusing SVM (about 23%) followed by ANN (15%), 8% on unsupervised learning and 11% towards probabilistic learning techniques as shown in Fig. 14. SVM can perform linear as well as non-linear classification and can also reduce the overfitting issue thus it has been utilized the most.

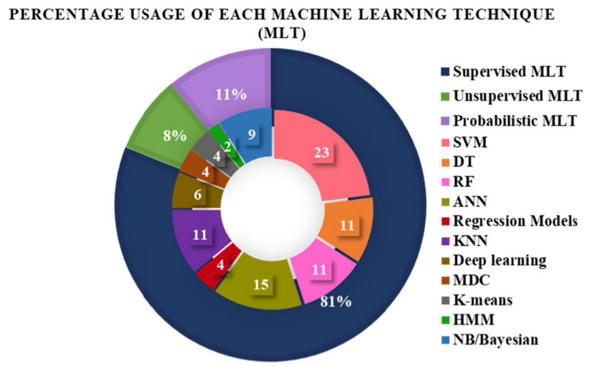


FIGURE 14. **The graphical representation of %age utilization of various MLT based on literature from (2005-2019) for PD evaluation.**

VI. PD GAIT DATASETS

The evaluation and development of a robust gait recognition model for the analysis of normal and pathological behavior heavily rely on an efficient database and other related factors. In recent years, a number of PD gait datasets have been created considering various conditions such as sample size (no. of subjects), walking scenarios (straight, turns), acquisition resources and environment (indoor, outdoor), frame size, etc. Based on the taxonomy shown in Fig. 5, total 6 such databases are obtained since1997, summarized in Table 6. Out of 6, one is vision-based and rest are based on the sensor. This section gives a very brief overview of gait datasets designed for PD diagnosis.

A. VISION-BASED PD GAIT DATASET

Focusing towards vision-based research on PD gait identification, only a single database is publicly available namely INIT gait database [12] (markerless). This database includes the sequence of binary silhouette (total 160 sequences) which are captured using 2D high definition video cameras in LABCOM studio. Ten volunteers (9 males, 1 female) were recruited to simulate seven different pathological gait patterns including PD and eighth style of a healthy and natural gait. They were asked to walk across a green color uniform background to capture high-quality data in order to enhance the accuracy of extracted features. Besides INIT database, most

TABLE 5. Summarizes mostly adopted categories of machine learning techniques (MLT) used in pd analysis with their benefits and drawbacks.

Technique used	Type of Learning	References	Pros/Cons
Support Vector Machine (SVM)	Supervised	[3,16,74,77,78,79,81,82,86,93,105,126]	(+) Decreases overfitting issue (+) Can handle complex problems via kernel function (-) Performance degrades on large datasets (-) Difficult interpretation and good kernel choice issue.
Decision Trees (DT)	Supervised	[15,52,89,91,99,121]	(+) Easy to understand and interpret (+) Deals well with missing data (-) Expectation based decision that can lead to inaccuracy
K-nearest neighbor (KNN)	Supervised	[15,52,78,79,82,93]	(+) Works well with large training samples (+) Simple and robust to noisy data (+) Easy implementation and no training step (-) High computational cost (-) Value of 'k' needs to be measured
Random Forest (RF)	Supervised	[73,77,79,95,97,124]	(+) Overcomes overfitting problem (+) Flexible, accurate and no need of data scaling (-) Difficult to interpret and time consuming
Artificial Neural Network (ANN)	Supervised	[51,52,69,71,78,81,82,124]	(+) Fault tolerance capability (+) Can generalize, handle noisy and incomplete data (-) Hardware dependent (-) Can't work with small dataset
Convolutional neural network (CNN), Recurrent neural network (RNN)	Deep Learning	[94,97,98]	(+) Improved accuracy (+) Weight sharing feature (-) Overfitting issue and requires larger data to work (-) Large computational cost
Linear Regression	Supervised	[50,96]	(+) Simple and easy (+) Resolves overfitting problem (-) Outliers sensitive
K- means, Minimum distance classifier (MDC)	Unsupervised	[14,48,76,95]	(+) Simple, fast and less computational complexity (+) Fix missing data problem (-) Difficult to choose cluster numbers (-) Inefficient to work with global cluster
Hidden markov model (HMM)	Probabilistic	[49]	(+) More flexible to fit the data (+) Provides good compression (-) Difficult to interpret and requires large memory and time
Naive Bayes (NB)/ Bayesian network	Probabilistic	[15,52,77,79,82]	(+) Simple, fast and easy implementation (+) Requires less training data (+) Performs probabilistic prediction (-) Risk of accuracy loss (-) Feature independency assumption

of the researchers created their own vision-based datasets privately and are not available (e.g. Eltoukhy *et al.* [13] developed their own database considering 11 normal and 8 PD affected subjects to inspect gait deviations). Thus, most of the datasets in vision-based PD gait diagnosis are private and have no access to the researchers.

B. SENSOR-BASED PD GAIT DATASET

The sensor-based dataset includes the behavioral signals (acceleration, force, pressure, etc.) of human body motion which are evaluated to perform effective gait analysis. The Physionet database [103] is the most preferred dataset to analyze PD gait. The reason is that it contains a huge amount of vertical ground reaction force data (VGRF's) obtained from large sample size (93 PD, 73 HC) using 16-foot sensors at 100 samples/size. Inertial measurement unit (IMU's) based dataset i.e. Daphnet FOG was first created by Bachlin *et al.* [100] to determine FOG events in PD subjects. This database consists of 10 PD subjects (7 males, 3 females) gait recordings in three scenarios: - straight walk with 180 degrees turn, random walk with 360 degrees turn and daily living activities (ADL). The collected acceleration signal data can be analyzed to perform gait classification. Therefore, the considered art-of-literature reveals public availability of sensor-based databases than vision-based datasets. The data provided in table 6 can be used to cope up with PD and other clinical disorders competently.

VII. FUTURE PERSPECTIVES

Research can't be considered efficient unless and until it is able to discover the unsolved issues in existing

TABLE 6. Summarizes year-wise creation of vision-based and sensor-based PD gait recognition datasets. Acronym of words used in the table: vision-based (VB), sensor-based (SB), Normal(NM), Parkinson disease(PD), Indoor(I), Hertz (Hz), electrocardiogram (ECG), galvanic skin resistor (GSR), near infra-red (NIR).

Dataset	Ref./Year	No. of subjects/ Gait type	Resource	Frame rate	Env.	Walking condition	VB/SB	Online Access Link
INIT	Ortells et al. [12]/ 2018	10/ NM	2D video camera	800*400 pixels (160seq.	I	Lateral view, normal and half motion of arms and legs	VB	http://www.vision.uji.es/gaitDB
CuPid multimodal dataset	Sinziana et al. [99]/ 2013	18/ PD	9 IMU's, 1 ECG sensor, a GSR and a NIR sensor	128 Hz	I	Diff. walking env.:- straight, passing via corridors, in crowded hospital hall, with 180 and 360 degree turns (24h)	SB	-
Daphnet FOG dataset	Bachlin et al. [100]/ 2010	10/ PD	Accelero-meter sensor	64 Hz	I	Straight walk with 180 deg. turn and random walk with 360 deg. turn, ADL	SB	https://archive.ics.uci.edu/ml /datasets/Daphnet+Freezing+of+Gait
Gait in ageing and disease database	- [101]/ 1999	15/ PD(5), HY(5) and HO(5)	Force shoe sensors	300 Hz	I	15 minutes (HC) and 6 minutes (PD) subjects walk on level ground	SB	https://physionet.org/physiobank/database/gaitdb/
Gait dynamics in neuro-degenerative disease dataset	Hausdorff et al. [102]/ 1997	64/ PD(15), HD(20), ALS(13) and HC (16)	Foot resistive sensors	300 Hz	I	77m walk for 5 minutes at normal speed	SB	https://physionet.org/physiobank/database/gaitndd/
Physionet	Hausdorff et al. [103]/ -	166/ NM(73), PD(93)	16 foot sensors	100 samples/ second	I	2 minute walk with self-selected speed on level ground	SB	https://physionet.org/pn3/gaitpdb/

art-of-literature. This forms the basis to carry out further research by proposing a robust approach in order to conquer the gaps pinpointed. Overtime, a number of vision-based Parkinson's disease (VBPD) identification approaches have been practiced and have attained promising outcome but still contain challenges that require further improvements for the development of more robust systems. Some specific future perspectives to deal with such challenges in VBPD recognition are as follows:

A. VB PD PUBLIC DATASET CONSTRUCTION

By exploring VBPD research in detail, only a single database i.e. INIT gait database [3], [12] (markerless) has been obtained that just contain few samples of normal subjects simulating the gait of some neurological disorders including PD. The effect of PD varies with age, gender and the severity of the disease. Simply considering simulated PD gait but not of actual patients gait (as in INIT), the reliability of the system may get compromised. Further, no such marker-based dataset is publicly available till now to the best of our knowledge. Most of the studies developed their own datasets possessing certain drawbacks also such as limited sample size [16], [48], no- consideration of gender disparity, unmatched demographic data, severity level ignorance [16], etc. and doesn't have any public access to them. Thus, this opens the door for the researchers to create new publicly available vision-based (marker-based as well as markerless) dataset with a large number of normal and PD subjects considering gender, age, and severity levels into focus so that more accurate investigation of PD can be performed.

B. ENHANCED PRE-PROCESSING

Once gait data has been gathered, it requires a sufficient amount of pre-processing to make it more valuable. In recent years, a number of issues such as the requirement of color contrast between subject's appearance and background [82], camera distortion [3], illumination and lighting conditions, etc. have been encountered by authors that make the pre-processing a tedious task and degrades the overall performance of the system. Khan *et al.* [16] proposed a markerless computer-vision based system to note the deviations in PD gait. The used approach proved to be feasible but was limited by the color segmentation method. So the future work can be directed towards the development of enhanced and effective pre-processing techniques that can handle such concerns and can perform robust background modeling for improved PD inquiry.

C. SELF-OCCLUSION/ OVERLAPPING CIRCUMVENTION

Self-occlusion or overlapping is still an insolvable problem that leads to inaccurate diagnosis with false recognition rate. During abnormal gait in PD, short shuffling steps make it very difficult to detect the gait deviations among left and right limb of the subject due to overlapping (one limb hides the

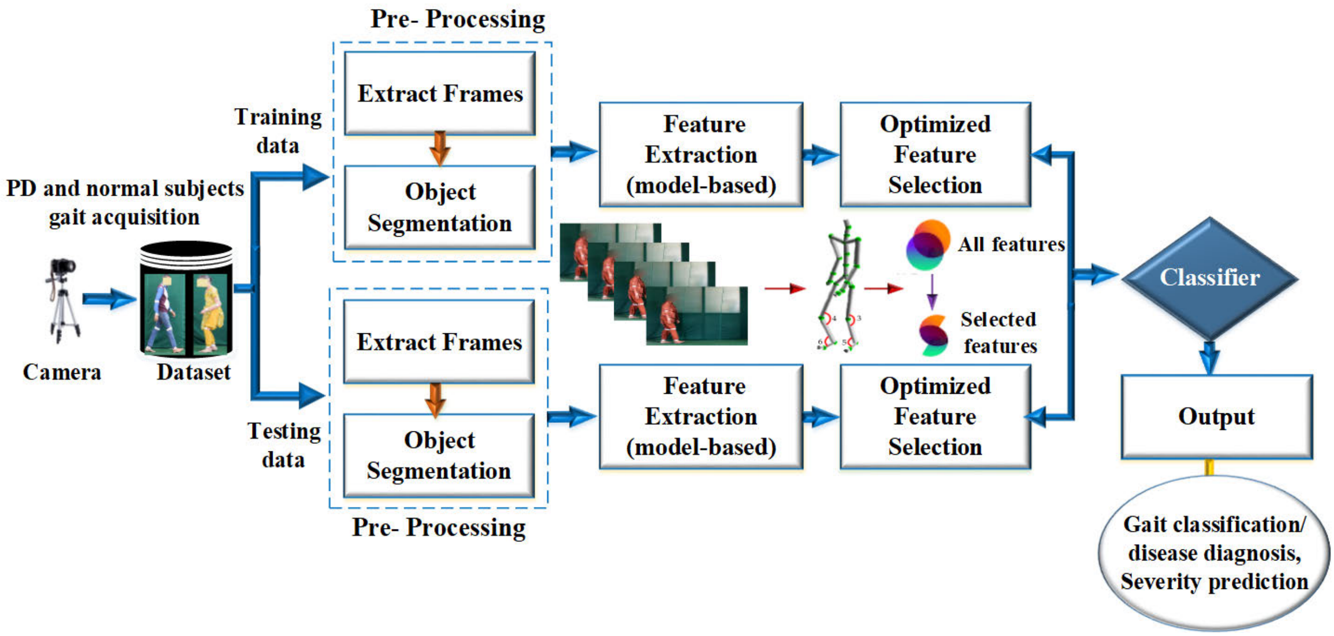


FIGURE 15. The proposed framework depicting the complete methodology for PD identification along with gait samples of PD (right person in the dataset) and healthy subjects (left person) in the sagittal plane (bi-directional).

other). Also, the arm movements play a significant role in providing useful clues regarding asymmetries in PD as arm become more still due to the resting tremor during walking. But the intersection of arms and legs in the extracted silhouette unclear the analysis of such differences in arm asymmetries among PD and healthy subjects. Shaw *et al.* [49] presented an approach to identify PD from silhouette using HMM. However, the system attained high accuracy rates but the arm motion was not able to be detected due to overlying. Similarly, Verlekar *et al.* [3], Ortells et al. [12] and Cho *et al.* [48] focused silhouette based PD recognition. The system classified normal and PD subjects giving promising results but the extracted silhouette was not clear and the arm movement of subjects was very challenging to analyze so it was not considered in an effective way. Therefore, efforts can be made in the future to resolve this issue by diving the subject into a number of components and again rebuilding the overlapped or occluded portions of the body using robust and more effective approach.

D. FEATURE SPACE MINIMIZATION

The use of a large number of features for evaluation purpose unnecessarily increases the feature space and often affects the recognition capability of the system. In spite, existing studies have used various dimensionality reduction algorithms including PCA [93], [104], LDA [78], [94], etc. for selection of optimized features for PD diagnosis but still need efforts to improve the system's efficiency. Thus, future work can be focused to address the feature space reduction issue by employing enriched feature optimization techniques (e.g. bacterial foraging optimization- BFO, particle swarm optimization- PSO, hybrid intelligence, etc.) to extract the most relevant set of PD gait features in order to enhance the classification accuracy. Hence, the aforementioned points should be given preference to perform improved and more reliable PD analysis that can be useful for their rehabilitation.

VIII. PROPOSED WORK

To tackle the challenges observed in vision-based markerless approach for PD gait identification, this section of the paper presents the framework of the proposed work depicting the complete methodology for robust PD analysis as shown in Fig. 15. We have proposed to focus on model-based identification of PD at different stages by classifying the PD subjects from normal controls. The methodology comprises of several stages which may lead to better performance and more accurate results.

The first stage is the marker-based (MB) gait acquisition of PD affected and healthy subjects. As it is discussed earlier in section VII that no such dataset is publicly available to work on. Thus, the purpose of this stage is to develop a new publicly available MB gait dataset considering actual PD patients and healthy subjects based on different severity levels (mild, moderate and severe), age, gender and disease duration considering sagittal plane.

The second stage is to preprocess the acquired gait data in order to extract the frames from videos, to eliminate noise and to segment the object. The model-free approach results in serious problems such as color contrast requirement, overlapping issue, background littering, etc. and thus require large amount of preprocessing. Therefore, the idea is to use model-based approach due to its robustness in handling such problems and can efficiently segment the object based on body joints for geometrical model construction without any need of complex preprocessing.

Once preprocessing is completed, the third stage of the methodology focusses on the extraction of diseased and normal subjects gait features, initially by rebuilding the overlapped objects (e.g. legs and arms occlusion) and then using MB approach for the purpose. Several gait features can be extracted but the combination of such features has shown the greater relevance to achieve good results. The fourth stage corresponds to the selection of best subset of features from all the extracted set of features. There exist various algorithms for this purpose such as PCA, LDA, genetic algorithm (GA), bio-inspired algorithms, etc. As GA has the greater capability to handle arbitrary kind of constraints and exhibits a unique property called elitism to select best feature but is susceptible to get trapped in local optima. To overcome this, the performance of GA can be enhanced by combining it with bio-inspired approaches like PSO which can prevent premature convergence by providing the global view of search space with less computational complexity. Thus, we propose to use hybrid intelligence of optimization techniques to get the best feature subset.

The fifth stage depicts the use of robust classifier to accurately differentiate normal and abnormal gait. The literature reveals the use of various traditional algorithms to achieve the purpose, but recently, to solve classification problem, deep learning (DL) is gaining high popularity due to its supremacy in terms of performance. Thus, we propose to apply DL model like CNN or generative Adversarial networks (GAN) which provide more accurate results. Finally, the last stage is to compare the obtained results with clinical PD assessment radiographic scores to check the reliability of the adopted system in determining severity among PD subjects. Thus, the proposed framework may present a robust solution to overcome the problems encountered in previous literature for PD detection.

IX. CONCLUSION

In recent years, the number of people suffering from PD has increased substantially and is recorded as the most deadly health issue worldwide. Making certain efforts, this article provides an exhaustive survey of existing research work concerning vision-based PD diagnosis through gait from 2005 to Feb. 2019.

The obtained literature revealed the prime focus on VB markerless technology (about 48%) where the Kinect sensor has been used the most for PD analysis due to its depth detail catching capabilities. The article precisely surveyed the preprocessing methods used to prepare PD gait data and also explored different categories of gait features that can be beneficial for PD gait evaluation. Amongst all, the fusion of PD gait features has been dominantly utilized as it enhances accuracy and provides a broader view for PD inspection.

In this work, several PD gait feature extraction and selection approaches are discussed. Data indicated the majority of research towards the use of PCA (almost 24%) for dimensionality reduction. Also, the article surveyed Machine learning techniques that have been used and SVM classifier is analyzed to be most adopted by researchers to classify PD and normal subjects (approx. 23%) to provide more effective decision-making.

Further, this article inclusively presented vision-based and sensor-based PD gait datasets. The surveying of articles from 1997-2019 yielded single database i.e. INIT gait database which is publicly available for VB PD analysis and rest are privately created by authors. Other publicly available datasets are based on sensor data.

Therefore, from the considered literature, it is concluded that towards VB, the markerless approach has been greatly preferred and can provide a more robust assessment of PD affected patients but still further research need to be done due to certain challenges such as overlapping/ self-occlusion, lighting conditions, color contrast requirement, etc. Finally, this article provides proposed work (model-based) that can be effectually deal with the identified gaps. Overcoming these issues can lead to amended performance with high accuracy. At last, a number of valuable references are given to extend the related research on PD in the future based on gait for practical experimentation also.

APPENDIX

Below the URLs for the images are provided that are taken from the internet and used in this survey article.

Figure 3: https://www.niehs.nih.gov/health/topics/conditions/parkinson/index.cfmhttp://prepareformedicalexams.blogspot.com/2016/11/regarding-clinical-features-in.htmlhttps://en.wikipedia.org/wiki/Micrographiahttps://www.missouribaptist.org/Medical-Services/Therapy-Services/Therapy-Services-Post/ArtMID/641/ArticleID/1391/Treatment-for-Parkinsons-Diseasehttps://in.pinterest.com/pin/501940320962463694/?autologin = truehttp://youandparkinsons.com/en-pk/view/m301-s03-treatment-and-management-of-parkinsons-disease-slide-show https://www.medindia.net/news/healthwatch/new-smell-test-for-detection-of-alzheimers-and-parkinsons-173687-1.htm https://www.healthline.com/health/parkinsons/sideeffects.

Figure 5: https://www.qualisys.com/hardware/accessories/pass ive-markers/soft-marker/https://docs.vicon.com/display/Nexu s25/Automatically+ assess+ foot+ strikeshttps://www.amazon.co.uk/Huawei-Y6-2018-Black-unlocked/dp/B07CG3P4DL https://www.youbeli.com/microsoft-xb360-kinect-sensor-black-new-p-1054887.html?stores = 1966https://www.frequencyprecision.com/products/floor-pressure-mat-kit-plug-matched?variant = 45400977109https://www.intorobotics.com/accelerometer-gyroscope-and-imu-sensors-tutorials/https:// www.miomove.com/shoe/https://www.cooking-hacks.com /electromyography-sensor-emghttps://newatlas.com/cityzen-smart-shirt-sensing-fabric-health-monitoring /30428/.

Figure 15: https://www.dhgate.com/product/wt-3110a-port able-lightweight-camera-tripod/407532459. html https://

dataaspirant.com/2018/01/15/feature-selection-techniques-r/https://www.mdpi.com/1424-8220/16 /11 /1792/html.

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