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# Recent developments in human gait research: parameters, approaches, applications, machine learning techniques, datasets and challenges

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**Abstract** Human gait provides a way of locomotion by combined efforts of the brain, nerves, and muscles. Conventionally, the human gait has been considered subjectively through visual observations but now with advanced technology, human gait analysis can be done objectively and empirically for the better quality of life. In this paper, the literature of the past survey on gait analysis has been discussed. This is followed by discussion on gait analysis methods. Vision-based human motion analysis has the potential to provide an inexpensive, non-obtrusive solution for the estimation of body poses. Data parameters for gait analysis have been discussed followed by preprocessing steps. Then the implemented machine learning techniques have been discussed in detail. The objective of this survey paper is to present a comprehensive analysis of contemporary gait analysis. This paper presents a framework (parameters, techniques, available database, machine learning techniques, etc.) for researchers in identifying the infertile areas of gait analysis. The authors expect that the overview presented in this paper will help advance the research in the field of gait analysis. Introduction to basic taxonomies of human gait is presented. Applications in clinical diagnosis, geriatric care, sports, biometrics, rehabilitation, and industrial area are summarized separately. Available machine learning techniques are also presented with available datasets for gait analysis. Future prospective in gait analysis are discussed in the end.

**Keywords** Human gait analysis · Machine learning techniques · Gait Datasets · Gait Approaches · Application · Survey

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## 1 Introduction

Walking is considered as one of the natural and common traits for the human being. But from the perspective of analysis, it is among one of the most complex phenomena. It is the combined effort of the brain, nerves, and muscles. Walking indicates liberty and individuality in humans thus any deviation from normal, can sternly reduce our quality of life (Nutt et al. 1993). Physiotherapists, orthopedists, and neurologists have been examining human motion for long to analysis and evaluated a patient's status, treatment and rehabilitation. Conventionally, the human gait has been considered subjectively through visual observations but now with technological advancement, human gait analysis can be done objectively and empirically.

Before discussion on the available gait techniques lets first look into the definition of terms gait and walking. Researcher Nutt et al. (1993) defines walking as coordinated movement of lower limbs with spanned flexion-extension in an involuntary and recurring fashion. The pattern of locomotion (walks, runs, crawls, etc.) combined with their posture is known as gait. Human gait provides a way of locomotion. As a species, the human is bipedal that is we move on two extremities. Most of the people tend to use the words gait and walking interchangeably. Gait is a way of walking, rather than the walking process itself. Whittle (2014) suggests that gait comparison makes more sense than walking comparison.

Research associated with human walking is known as gait analysis. It is a systematic technique for recognizing negative deviations in the gait pattern and determining their reason and effects. Gait Analysis is a way to reveal the mechanisms of human movement by quantifying factors governing the functionality of the lower extremities. Human gait analysis has numerous uses, such as medical diagnostics, security, animation, industry and sports science (Johnson and Bobick 2001; Prakash et al. 2015a). In gait analysis for medical recovery, optical-based motion analyzer systems have been widely used to monitor a patient's response.

Dysfunctional gait can arise from acute or chronic injury or either because of improper bio-mechanics. Physiotherapists and orthopedists can monitor and analyze gait movement variables i.e. stride length, step length, cadence, stance and swing phase, etc. of such patients, to point out if improvement has taken place.

According to United Nations (Fuhrer 2014), Asia is a home to close to two-thirds of the world's population of physically challenged and this digit is expected to climb over the next decade. However now with combining advanced measurement technology and biomechanical modeling, there are more opportunities for better quality of life for the disabled community worldwide. The desire to improve the quality of life and reliability of rehabilitation drives new research and development activities in several countries. The empirical and quantitative analysis of gait variability using kinematics and kinetic characterizations can be helpful to healthcare professionals in both predicting onsets of a condition and monitor patient's recovery status in clinical applications. Moreover, these quantitative results may help to strengthen their confidence in the rehabilitation.

Human motion analysis is a challenging problem due to variations in human movement and appearance, camera viewpoint, and environment settings. A major section of researchers, fascinated by this area proposed new techniques. Table 1 epitomizes visual overview of relevant surveys and articles published in past two decades, on human walking analysis. Review by Aggarwal et al. (1994) was perceived as the first notable review paper on gait analysis study.

The reader can get an overview of important available gait analysis surveys and article papers from Table 1. Papers are arranged in order of year of publication and approach either

**Table 1** Analysis of previous gait analysis surveys

| Year | Author | Comment/focus | VB | SB |
|---|---|---|---|---|
| 1994 | Aggarwal et al. | Priori shape and model based articulated and elastic non rigid motion | ✓ | ✓ |
| 1995 | Cedras and Shah | Extraction of Motion information from frame and recognize activity | ✓ | |
| 1996 | Ju | Motion estimation and recognition | ✓ | |
| 1996 | Whittle | Gait analysis considering video based, EMG, kinematics, kinetics parameters for clinical purpose | ✓ | ✓ |
| 1998 | Aggarwal et al. | Articulated and elastic non rigid motion | ✓ | ✓ |
| 1999 | Aggarwal and Cai | Human motion tracking, analysis and recognizing activity using single/multiple cameras | ✓ | |
| 1999 | D. M. Gavrila | Recognize humans and their activities, applications | ✓ | |
| 2001 | Chau | Explore application of fuzzy, multivariate statistical and fractal technique for gait data | ✓ | ✓ |
| 2001 | Chau | Neural network and wavelet method for gait data | ✓ | ✓ |
| 2001 | Moeslund and Granum | Initialization, tracking, pose estimation, and recognition techniques in last 2 decade | ✓ | |
| 2001 | Sutherland | Discuss EMG methods to gait applications | | ✓ |
| 2002 | Sutherland | Focus on Kinematics methods for gait applications | | ✓ |
| 2003 | H. Buxton | Model for interpretation of a dynamic scene | ✓ | |
| 2003 | Wang and Singh | Human tracking and modeling behavior related approaches | ✓ | |
| 2003 | Wang et al. | Human detection, tracking, and activity recognition | ✓ | |
| 2004 | Aggarwal and Park | Human recognition | ✓ | |
| 2004 | Hu et al. | Gait analysis in surveillance | ✓ | |
| 2005 | Sutherland | Focus on kinetics and energy assessment to gait applications | | ✓ |
| 2006 | Baker | Methodologies for gait analysis in a clinical rehabilitation | ✓ | ✓ |
| 2006 | Moeslund et al. | Initialization, tracking, pose estimation and recognition | ✓ | |
| 2007 | Owusu | Computational technologies for sports | ✓ | ✓ |
| 2007 | R. Poppe | Modeling and pose estimation | ✓ | |
| 2007 | Kruger et al. | Classification of human action representation, recognition, synthesis and understanding of action | ✓ | |
| 2008 | Turaga et al. | Human activity analysis-approaches based on complexity | ✓ | |
| 2008 | Vasconcelos et al. | Computational techniques in human motion analysis | ✓ | |
| 2009 | Lai et al. | Computational techniques with application in gait analysis | ✓ | ✓ |
| 2009 | Liu et al. | Video based gait recognition | ✓ | |

**Table 1** continued

| Year | Author | Comment/focus | VB | SB |
|---|---|---|---|---|
| 2010 | Mannini and Sabatini | Classification of human physical activity | ✓ | ✓ |
| 2010 | Wang et al. | Gait recognition Techniques | ✓ | |
| 2010 | Morris and Lawson | Gait analysis technologies and study of impact transmission | ✓ | |
| 2011 | Zhaoxiang Zhang et al. | Gait recognition | ✓ | |
| 2011 | Aggarwal et al. | Compare different types of complex human activity recognition approaches | ✓ | |
| 2011 | Chai et al. | Human gait recognition datasets approaches | ✓ | |
| 2012 | C.B Ng et al. | Gender recognition | ✓ | |
| 2012 | Tao et al. | Human Kinematics kinetics parameters from wearable sensors | | ✓ |
| 2014 | Alvaro et al. | Overview of Wearable and Non-Wearable Systems for clinical applications | | ✓ |
| 2014 | Gowsikhaa et al. | Human behavior recognition | ✓ | |
| 2014 | Shirke et al. | Model free gait recognition approach | ✓ | |
| 2014 | Tracey K. M. Lee et al. | Technologies in Gait analysis and recognition | ✓ | |
| 2015 | Wright and Jordanov | Computational techniques for legged locomotion | ✓ | ✓ |
| 2015 | Connie et al. | Cross and multi-view gait recognition | ✓ | |
| 2016 | This survey | Gait analysis approaches, machine learning techniques, applications and available datasets for gait | ✓ | ✓ |

Vision Based (VB) or Sensor based (SB) are also mentioned in this table. Table 1 suggests that gait analysis is an emerging research area with an application in clinical pathology and biometrics. Researchers are now trying to understand the scene based on the activity of the subject in the video frame.

The purpose of this comprehensive study on contemporary gait analysis is to discuss the parameters in gait analysis, available techniques, machine learning techniques and available database for gait analysis. The paper is drafted in the following manner: Section 2 provides an overview of essential taxonomies and representation techniques of human gait available in articles. Section 3 details human gait analysis approaches. Section 4 discusses the different application domains of gait analysis. Section 5 focuses on the available machine learning techniques. Section 6 presents the datasets available for gait analysis. Section 7 provides the conclusion and future perspective in vision based gait analysis.

## 2 Basics of human gait

Gait is considered as stereotyped activity in both young and old healthy people. Gait is known as the pattern of locomotion along with posture. Gait analysis is the research associated with human walking, and it reveals the mechanisms of human movement by quantifying factors governing the functionality of the lower extremities.

## 2.1 Gait cycle

Walking is considered as a series of cyclic events known as gait cycles. For understanding pathology, normal gait pattern is essential to be able to detect alteration in gait.

Weber brothers use the concept of the gait cycle and calculate the timing of gait in 1836. A gait cycle consists of the activities that occur from the point of initial contact of one lower extremity to the point at which the same extremity contacts the ground again. Gait cycle is a combined function of the lower extremity, pelvis, and spinal column. It is a single sequence of functions by one limb. It begins when reference foot contacts the ground and end with subsequent floor contact of the same foot. A single gait cycle is known as a STRIDE.

Dysfunctional gait can arise from acute or chronic injury or either because of improper biomechanics. It prohibits normal weight-bearing competence on the bipedal and influences stresses placed on joint surfaces.

Gait cycle begins with heel contact of either foot and ends with the heel contact of the same foot. Therefore, one complete gait cycle consists of two steps one of either right foot and then left or vice versa. By convention, normal gait cycle is the period in which heel of one foot contacts the ground to when the heel contact of the same foot takes place, and forward propulsion of the center of gravity is involved.

A single gait cycle consists primarily of two phases: a swing phase and a stance phase (Perry et al. 1992). In general, stance phase begins with the heel contact and ends with the toe off of the same foot. That duration when foot remains in contact with the ground is known as stance phase and accounts for approximately 60 % of the normal gait cycle. The duration when the foot is off the ground is known as swing phase and accounts for 40 % of the gait cycle. Swing phase begins with the toe off of the delete foot and ends with the heel contact of that same foot.

Stance phase and swing phase could be further segmented into eight segments and are referred as critical incidents which enable the examiners to specify further the abnormal aspects of gait. Classical gait model by Perry divides gait cycle into eight sub-phases (five stance and three swing) (Perry et al. 1992). Further, stance phase is divided among five sub-phases: Initial contact, Loading response, Mid Stance, Terminal Stance and pre-Swing whereas swing phase has three sub-phases: Initial Swing, Mid Swing and Terminal Swing. Figure 1 shows the fundamentals of gait phases and expected interval of phases and sub-phases in the total gait cycle. In this study, the right foot is considered as the reference foot for gait phases cycle and is shown in the black shade in Fig. 1.

*Phase 1: Initial contact (IC)* It is considered as the point at which the heel of the reference foot touches the ground. Thus, it is also known as heel strike. It is the beginning of the loading response, which constitutes 0–2 % of the total gait cycle as shown in Fig. 1a.

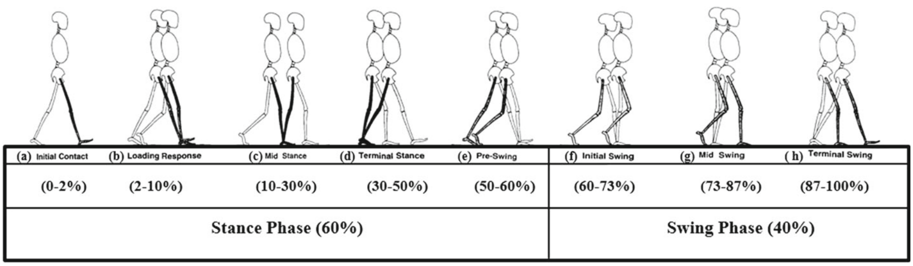


**Fig. 1** Fundamental gait phases and expected interval of gait cycle (Perry et al. 1992)

*Phase 2: Loading response (LR)* It begins with the initial contact of the reference foot and continues until the other foot is lifted for swing. During this period the reference foot comes in full contact with the floor and body weight is fully transferred onto the stance limb and accounts for 2–10 % of total gait cycle, as shown in Fig. 1b.

*Phase 3: Mid-stance (MSt)* It begins with contralateral toe (one opposite the reference foot toe) off and ends when the center of gravity is directly over the reference foot. It begins when tibia of the swing leg is upright to the ground, and its share is 10–30 % in the total gait cycle.

*Phase 4: Terminal stance (TSt)* Its share is 30–50 % in the gait cycle and is initiated by moving into hip extension until just before pre-swing as shown in Fig. 1d. It is the point at which COG is over the reference foot and ends when the contralateral foot touches the ground.

*Phase 5: Pre-swing (PSw)* It accounts for 50–60 % of the total gait cycle as shown in Fig. 1e. It is considered to begin when contralateral toe is in Initial Contact and ends with toe-off.

*Phase 6: Initial swing (ISw)* This is the first phase of swing and accounts for 60–73 % in the gait cycle. In this phase, hip of the reference foot is in, flexion and the corresponding knee stays in flexion mode.

*Phase 7: Mid swing (MSw)* This is considered to be the second phase of swing and in this phase, the flexion of the reference foot knee is at the extreme. It constitutes 73–87 % of the total gait cycle.

*Phase 8: Terminal swing (TSw)* This is the phase when the tibia is perpendicular to the ground. Its share is 87–100 % in the gait cycle and ends at IC.

Initial contact and loading response can be considered as the same phase as former is an instance of loading response only. It is seen that different pathologies affect different segments of either swing or stance phase. Any abnormality suggests that there is a pathology, which should be identified by the examiner.

Each gait phase has a functional objective and a critical pattern of selective synergistic motion to accomplish its goal. The sequential combination of the phases also enables the limb to perform three basic tasks, namely, weight acceptance, single-limb support, and limb advancement. Weight acceptance begins the stance period through initial contact and loading response. Single-limb support continues the stance through the midstance and terminal stance. Limb advancement starts as the pre-swing phase and continues through initial swing, mid-swing, and terminal swing. Based on gait cycle analysis one can analyze the abnormal gait behavior. Fuzzy logic can be used to analyze the abnormality as presented in Prakash et al. (2016a).

## 2.2 Parameters in gait analysis

Dysfunctional gait can arise from acute or chronic injury or either because of improper bio-mechanics. Physiotherapists and orthopedists can monitor and analyze gait movement variables. Thus, it is essential to provide a brief discussion on the parameters used in gait analysis. Literature survey suggests that there are six categories of possible parameters used in gait analysis. Muybridge et al. (1887) were the first one to study the gait mechanism. They studied gait of a running horse, known as Horse in Motion.

Gait analysis includes the measurement of temporal, Kinematics, Kinetics and Dynamic Electromyography(EMG) based parameters from which conclusions about the subject (health, age, size, weight, speed, etc.) can be drawn (Collins et al. 2002). Figure 2 shows the comprehensive parameter tree in gait analysis.

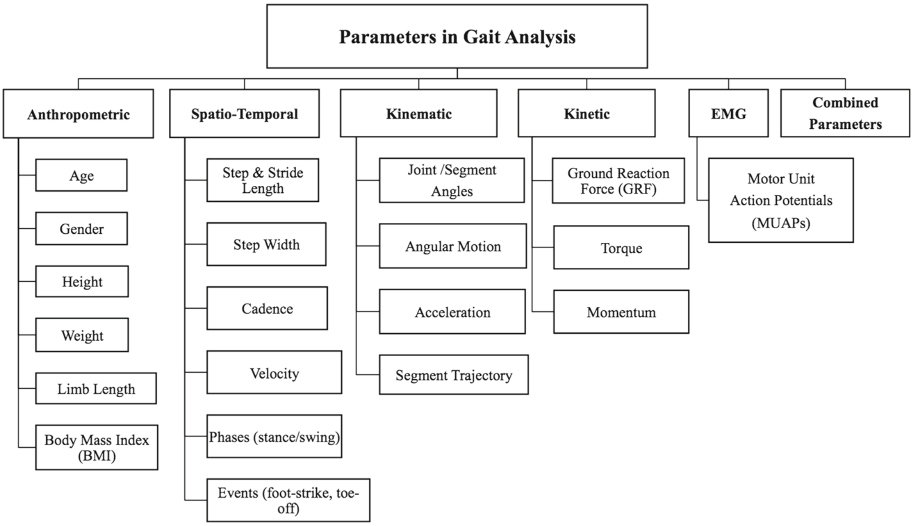


**Fig. 2** Comprehensive parameter tree in gait analysis

*Anthropometric parameters* The anthropometric parameters usually consider corporeal dimensions of the human including age, gender, weight, height, limb length and Body Mass Index (BMI) of a subject. Researchers advocate group based analysis on the similar anthropometric parameters for gait analysis. It is essential to isolate anthropometric effects on gait analysis.

*Spatio-temporal parameters* Spatio-Temporal are also known as general gait parameters. They are responsible for providing the simplest form of objective gait evaluation (gait specifications). Gait analysis system considers time-distance parameters such as step and stride length, step width, cadence, velocity, phases (stance and swing) and foot strike and toe-off events for spatiotemporal. It also includes walking base, toe-out angle, foot contact pattern. Among them, the stride length is most important and useful gait parameter for both medical and computing field. Table 2 lists some of the definitions of terms used in gait analysis.

*Kinematic parameter* Kinematic parameters are the measures of movement or geometric description of motion of body segments It is the movement of the body in space without any reference to forces. It includes joint angles by considering the motion of body landmark selected for analysis. Along with angle of joints (trunk angle, hip angle, knee angle, ankle angle, etc), it also comprises angular motion, acceleration and segment trajectory. Usually, markers and sensors are used to measure these parameters as discussed by Sutherland (2002), Prakash et al. (2015a). Electromagnetic systems track coordinates (X, Y, and Z) and orientation is also considered.

*Kinetic parameter* It is the group of forces involved in producing ground reaction forces (GRF), torque, pressure patterns and joint forces. Force platforms are used to measure three-dimensional force components. Researchers consider mass, center of gravity and momentum (Sutherland 2005; Muro-de-la Herran et al. 2014).

**Table 2** Definitions of some of terms used in gait analysis

| Terms | Definition |
|---|---|
| Body Mass Index (BMI) | It is the ratio of body weight (kg) divided by the square of the body height (m) |
| Single-support duration | Interval when one foot is in contact with the ground |
| Double-support duration | Interval when both feet are on the ground |
| Step length | Distance between corresponding successive points of heel contact of the opposite feet |
| Stride length | Distance between consecutive points of heel contact of the same foot. In normal gait, it is double of step length |
| Cadence | Rate at which a person walks. It is number of steps per unit time |
| Velocity | Distance covered by the body in unit time. Usually measured in m/s |
| Phase | Walking can be considered as a set of repetitive components known as phases. Classical gait model by Perry divides Gait cycle into 2 phases (stance and swing) |
| Event | Two types: Foot strike and toe-off. Foot strike is point of contact of foot with ground while toe-off is the point when foot is off the ground |

*EMG parameter* It is used to study the muscular activity during walking. Needle or surface EMG electrodes are used to record motor unit action potentials (MUAPs) (Kunju et al. 2009).

*Combined parameters* For better analysis and visualization, researchers attempt to combine aforementioned parameters such as joint angles and ground reaction forces with the anthropometric measures (Lai et al. 2009a).

Selection of accurate gait parameters is very crucial in gait analysis as the outcome of research depends greatly on choosing the most appropriate gait features. The factor of interest among the discussed parameters depends on the field of research for example in the field of sports; EMG parameter is best suited to analyze force applied on muscle.

## 2.3 Normal gait

Dysfunctional gait can arise from acute or chronic injury or either because of improper biomechanics. Physiotherapists and orthopedists can monitor, and analysis gait movement variables i.e. stride length, step length, cadence, stance and swing phase, etc. of such patients, to point out if improvement has taken place. Further, these procedures can be compared against age and sex-matched normal gait population distributions to decide whether the patient is exhibiting normal representation or not. Physiotherapists, orthopedists, and neurologists use quantitative gait parameters for better realization of patient's gait pathology (Mahyuddin et al. 2012; Prakash et al. 2015d). Availability of quantitative gait parameters is essential for the detection of gait disorders, identification of balance features, and assessment of medical gait interventions and rehabilitation developments.

Defining normal gait pattern is a very tedious task. Research suggests for group wise analysis to find the normal pattern. Table 3 presents healthy gait parameters for different range proposed in the literature. Ranges are indicative of subject population and do not necessarily hold for the general population. It may vary from region to region (Lai et al. 2009b).

**Table 3** Healthy gait parameter for different age group (Lai et al. 2009b)

| Parameters (self-selected pace) | Young (1–7) | Adult | Elderly (>65) |
|---|---|---|---|
| Walking velocity (m/s) | 0.64–1.14 | 1.30–1.46 | Declines 15 % per decade |
| Stride length (m) | 0.23–0.57 | 1.68–1.72 | 1.66–1.70 |
| Step length (m) | 0.20–0.32 | 0.68–0.85 | 0.44–0.60 |
| Stance phase (s) | 0.32–0.54 | 0.62–0.70 | 0.68–0.72 |
| Swing phase (s) | 0.19–0.27 | 0.36–0.40 | 0.42–0.44 |
| Cadence-fast walking (steps/min) | 176–144 | 113–118 | 58–70 |
| Single-support (% of stride) | 64.4–65.6 | 60.6–62.0 | 61.7–62.9 |
| Double-support (% of stride) | 22.5–23.9 | 21.2–23.8 | 23.4–25.8 |

## 2.4 Abnormal gait

Dysfunctional gait can arise from acute or chronic injury or either because of improper biomechanics. It prohibits normal weight-bearing competence on the bipedal and influences stresses placed on joint surfaces.

Lai et al. (2009b) suggests clinical and elderly gait disorders as two types of common gait disorders. Clinical gait disorders include limping movements such as antalgic gait patterns arise due to lower segment pathology such as knee osteoarthritis tendon rapture and patellofemoral pain syndrome. The pain is due to abnormal weight-bearing competence either on ankle or knee joints. Patients exhibit short stance phase. The second type of disorder is apraxic gait which, arises due to deterioration of neurons(nerve cell) and motor system responsible for human locomotion control. Alzheimer, Parkinson, Cerebral Palsy (CP), Freezing of gait and dementia are the examples of this apraxic based gait pathology and is characterized by loss of ability to move properly (Joshi et al. 2010; Mazilu et al. 2013). Ataxic gait is considered as the third general disorder where there is a loss of sense of relative limb positions and characterized by unsteady and uncoordinated walking feet pointed outward. It is due to chemical intoxication such as medial or alcohol or cerebral disease.

Nearly 50 % of people over age 65 have gait problem. Senile gait pattern is the best example of gait disorder arising due to normal aging (Zhang et al. 2014; Fukuchi et al. 2011). Subject exhibits broad stance and reduced gait velocity. Frontal lobe gait pattern arises due to injury in frontopontocerebellar tract Cerebrocerebellar system and Arnold's bundle and is characterized by balance disorders.

In sensory ataxic gait pattern, sensory inputs are averted to brain. This pattern results in the decrease in visual activity, proprioception and depth perception. Also, elderly people exhibit waddle gait patterns due to either back or pelvis muscle breakdown. Such type of pattern is known as myopathic gait. The elderly population is faced with gait disorder progression, which increases the risk of death precipitated by falls and bone fractures.

# 3 Human gait analysis approaches

Gait analysis is not a new research area. A systematic study of gait started with the description of walking principle by Leonardo da Vinci, Galileo, and Newton. In 1682, a student of Galileo, Borelli described how balanced walking could be achieved using the concept of center of

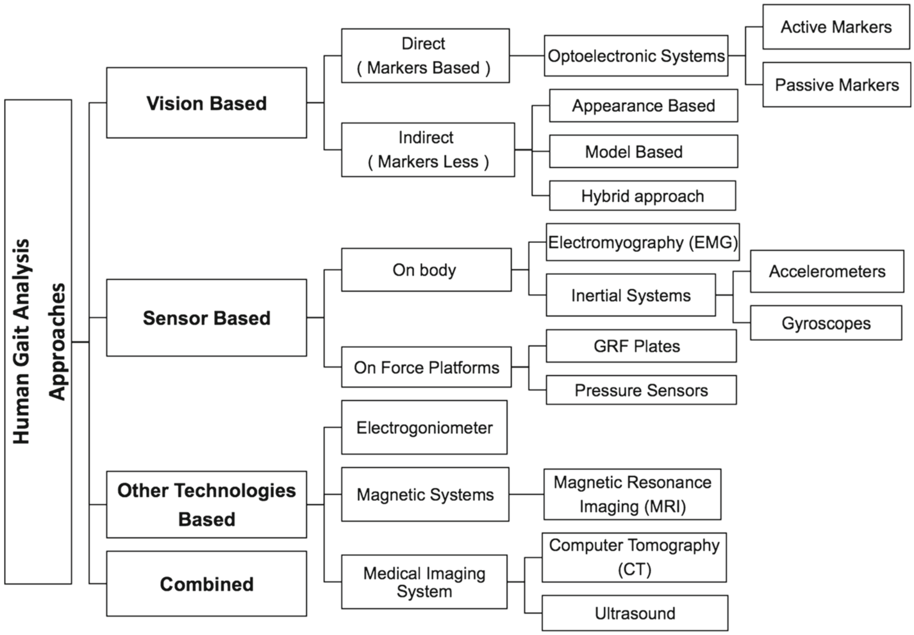


**Fig. 3** Available gait analysis: a comprehensive tree diagram

gravity of the body. In 1878, Edward Muybridge and Leland Stanford were the first ones to study the gait mechanism (Whittle 2014). Even though considerable research has been done in gait analysis area, still it has not yet been fully utilized. With the evolution of new models and methods, gait analysis research is an ongoing activity. Since 1960, clinical gait analysis gained momentum with the advent of new computational techniques. The researcher has proposed numerous approaches for the gait analysis (Vasconcelos and Tavares 2008).

After intensive research, we can claim that contemporary human gait analysis approaches can be broadly classified into four types: Vision Based or Image Processing based using a video camera, sensor-based and other technologies and combined approaches as shown in Fig. 3.

### 3.1 Vision based approach

The video camera is used to capture frames in vision based gait analysis approaches. This analysis can be accomplished by two methods; with (direct) or without markers (Indirect) on the subject. Analog or digital cameras are used to analyze gait. Vision-based approach are used to recognize gait, segment position and gait phase detection as presented by Moeslund and Granum (2001), Whittle (2014), Aggarwal and Cai (1999), Poppe (2007), Moeslund et al. (2006), Little and Boyd (1998), Prakash et al. (2015a, c).

Marker-based approach is also known as direct vision based approach (Lee et al. 2014). It is a popular method to find the kinematics of a human. Active or passive markers were developed to perform real-time direct vision based gait analysis (Wang et al. 2010). Direct gait analysis technique uses an optoelectronic system. Optoelectronic systems convert light signals into electrical signals and track the light emitted or reflected by markers. Active markers emit a signal and come in the form of small light-emitting diodes (LEDs) that can be attached to the subject. The cameras send out infrared light signals and detect the reflection from the markers attached to the body. This signal is used to locate the position of the marker as individual markers work at predefined frequencies. The accuracy of these systems is commendable, given the fact that they can often locate markers uniquely within a distance as small as 1 mm. However, such systems have their disadvantages such as the subject's natural motion is hindered due to the presence of cables or other components that can affect their gait pattern. Passive markers reflect light emitted by the cameras back to them and near infrared light is used to illuminate the markers. Passive markers are spheres covered with reflective scotchlite™ tape. They are specially designed to reflect incident light directly back along its line of incidence.

The researchers propose numerous viewpoints for observation of gait abnormality but all agree on two best views (sagittal or lateral and frontal or back) for observation of gait abnormality. For 2D and 3D analysis, many camera-based motion capture systems are available in the market. One camera is decently enough for two-dimensional analysis. The camera is positioned in sagittal view (perpendicular to the walkway), but this approach has a limitation that it is unable to capture all out of plane motion. Three-dimensional analysis can overcome this limitation, but in that there is a need for more than one camera. To project the three-dimension model, a point of interest region of the subject should be visible by at least two cameras simultaneously (Morris and Lawson 2010). Across the world, leading gait labs use four to eight cameras.

The indirect approach in vision based gait analysis doesn't use markers. From the video captured, through video camera either based on the model, appearance or hybrid approach can be used to analyze the features of the subjects (Lu et al. 2014; Hu et al. 2004). This is the most common approach in human recognition based on human gait in surveillance.

### 3.2 Sensor based approach

Gait analysis can be performed, by using the sensor, placed either on the subject body or, on the floor (Muro-de-la Herran et al. 2014; Tao et al. 2012; Ngo et al. 2014). Surface or middle based electromyography (EMG) and inertial systems are placed on the body of the subject. Force Platform is also used to obtain the kinetics of the subject's movement.

EMG is used to study the muscle electrical activity during walking, and it can be used to detect gait phase. Needle or surface EMG electrodes are used to record Motor Unit Action Potentials (MUAPs) (Sutherland 2001). Even for a single movement, a group of muscles is involved. The amplitude of EMG signals derived during gait may also be interpreted as a measure of relative muscle tension but there is a need for specific knowledge on electrode setup, and they are sensitive to interference.

Inertial systems are based on a principle of resistance towards change in motion. Accelerators and gyroscopes are used to measure inertia and segment orientation respectively. The sampling rates used for gyroscopes are similar to that used in accelerometers. Some researchers propose to use gyroscopes with accelerators to get the kinematics of the subject's movement (Mannini and Sabatini 2010; Zhang et al. 2014). They can be used to find segment position, step detection, and stride length. It is sensitive to interference and the algorithms are complex in nature.

Floor platform based sensors are used to obtain forces involved in producing ground reaction force, force pattern, foot plantar pressure distribution, step and gait phase detection (Sutherland 2002; Frenkel-Toledo et al. 2005). Ground Reaction Force (GRF) plates are used to calculate force magnitude and direction when the foot contacts the force plate. Force applied on GRF plates is sensed by transducers (with steel plate) attached on each corner of the plate. This force is converted to an electrical signal, and it is used to calculate the center of pressure, three orthogonal force component of subject's movement.

Pressure sensors are used to get the load details applied on sensors (Alaqtash et al. 2011). They are placed inside insole of shoes. When mechanical strain is applied to these piezoelectric-based sensors, they generate an electrical signal. Healthcare professionals can identify gait phase with these methods, but there is a limitation of space, in these technique. For correct measurement, subjects need to keep their foot on the center of a plate of floor platforms; this makes the subjects conscious, and they are not able to exhibit their normal pattern. Another limitation is in terms of cost. Even the well-equipped gait labs have only two or three plates at maximum. Thus healthcare professionals are not able to capture the regular pattern of the subjects.

### 3.3 Other technologies

Other technological based approaches such as Electrogoniometer, magnetic and medical imaging based systems can be used as a human gait analysis approach. By evaluating the change in resistance of potentiometer with two rotating arms in Electrogoniometer, one can perform the analysis of the joint angle change and step detection. There should be precise calibration of potentiometer before using it for analysis. This Electrogoniometer based approach is inappropriate in a time constrained environment as it consumes time to attach to a subject.

Magnetic system based approach doesn't need a line of sight for the markers as is required in vision based marker approach as it operates using a magnetic field to track ferromagnetic markers. Movement of the segment and anatomical data of subject's segment can be obtained by using Magnetic resonance imaging (MRI), computer tomography (CT) and ultrasound. It is then used to customise a computational model of the subject to which kinematic and kinetic data can be applied (Schöllhorn et al. 2008; Nordin and Frankel 2001). These systems are also sensitive to interference.

### 3.4 Combined/hybrid approach

Besides these approaches, there is also another hybrid approach that uses a combination of two or more aforementioned approaches. Researchers have used vision and EMG and force platform for better analysis of human gait (Schöllhorn et al. 2008; Begg and Kamruzzaman 2005; Heinen and Osório 2006; Prentice et al. 2001; Begg and Kamruzzaman 2006; Zhang et al. 2014).

## 4 Application domain

Early work by Vasconcelos and Tavares (2008) discuss the applications domains in gait analysis. In this section, we discuss the state of the art within the possible application of gait analysis. Gait analysis applications can be clustered under five titles: Analysis, Biometric, Artificial Gait, Control based and other application as shown in Fig. 4.

### 4.1 Analysis based application

Identification of normal gait pattern, medical diagnostic, geriatric or older person care and sports monitoring and tactics are part of gait analysis based application. Availability of quan-

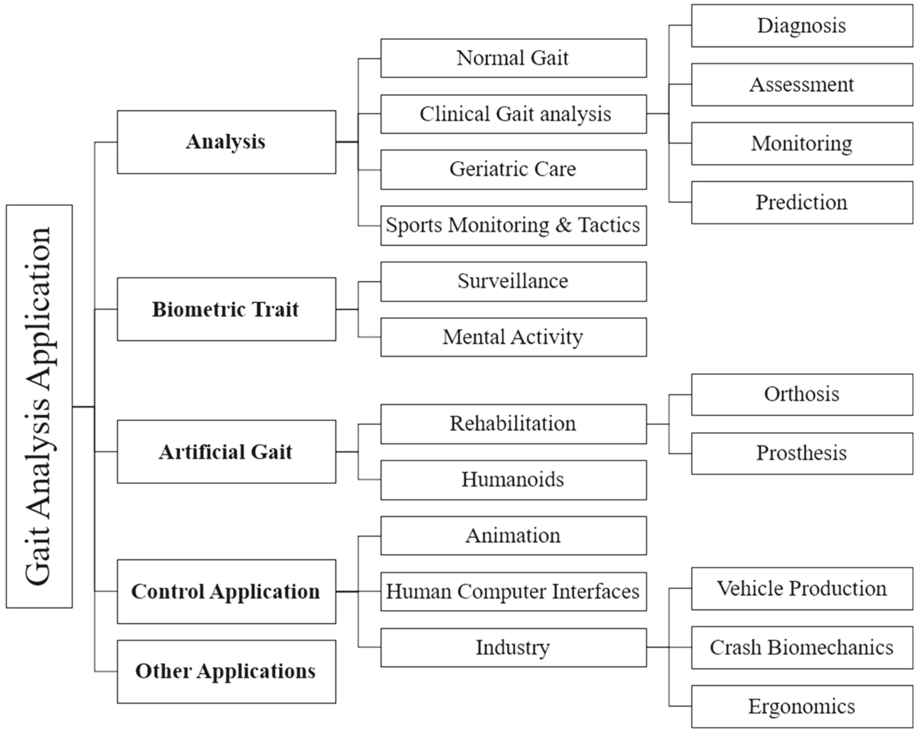


**Fig. 4** Application of human gait analysis

titative normal gait parameters is essential for the detection of gait disorders, identification of balance features, and assessment of medical gait interventions and rehabilitation developments. Health-care professionals can utilize gait phase recognition concept in their routine practice to identify the abnormality (Lai et al. 2009a). Extrinsic factors (terrain, footwear, clothing, and cargo), intrinsic (sex, weight, age), physical, psychological (type of personality and emotion) and pathological factors (such as neurological disease, trauma, musculoskeletal and psychiatric) influence Normal walking (Begg and Kamruzzaman 2006; Alaqtash et al. 2011). Even a single individual retains a wide-ranging gait behavior, thus determining this normal gait parameters range is a very complex and intricate task. It is difficult in pathological gait diagnosis (Song et al. 2013).

The technique that deals with the identification of hidden impairments and has an effect on gait patterns is known as Clinical Gait Analysis (CGA). Identification of pathological gait is the most unswerving implementation of gait analysis. Clinicians can utilize gait segmentation concept in their routine clinical practice to evaluate a patient's status, treatment, and rehabilitation for complex musculoskeletal and neurological disorders using the spatio-temporal and kinematics parameters. Healthcare Professionals can monitor the progress of the patients by comparing with the standard norms gait pattern and their past records. By comparing the normal and current gait cycle phase pattern, healthcare professionals can suggest effective treatment. Gait analysis can be implemented to cure pathologies such as Cerebral Palsy (CP), Parkinson's disease (PD), dementia stroke, patellofemoral pain syndrome, knee osteoarthritis and tendon rapture, Freezing of gait (Skelly and Chizeck 2001; Lai et al. 2009c; Tirosh et al. 2010; Joshi et al. 2010; Mazilu et al. 2013).

It can be used as an appliance for kinesiology for movement disorder. It can be used to analyze healthy subjects and can be used as a preventative health screening context, for example, it can be used to detect the risk of fall in elder persons. Problems of postural defects and walking Gait in elder adults (also known as senile gait) have become more substantial and of greater concern (Begg and Kamruzzaman 2006).

Nearly 50 % of people over age 65 have gait problem. Each year approximately 33 % of Australians aged over 65 years' experience a fall and half this number fall more than once. USA corroboratively asserts that that more than 30 % of people aged 65 or above and living in the community fall each year, Canadian statistics indicate indicate that one-third to one-half of people over 65 are prone to falling, Hong Kong to be 19.3 % per year, with recurrent falls happening in 4.75 % of Chinese older adults every year, prevalence of falls as varying from 21.6 % in Bridgetown (Barbados) and 29 % in Havana (Cuba) to 33 % in Mexico City (Mexico) and 34 % in Santiago (Chile). In addition to the physical and psychological trauma, there is an annual financial cost of falls-related injuries exceeding $3 billion. For example, 90 % of adults with cerebral palsy (CP) in the U.S. were alarmingly found to lack access to periodic health checks even though more than half of hemiplegic CP cases were known to require constant personal assistance as presented by Prakash et al. (2015d).

Half of these fallers cannot get backup without assistance and if left unattended for more than two hours run the risk of dehydration, hypothermia, pneumonia, pulmonary embolism (38 % of deaths in hip fracture falls), rhabdomyolysis (toxic breakdown of muscle fibers), and pressure ulcers. Rapid growth in the proportion of the population over 65 years will accelerate falls-related healthcare costs. This results in loss of independence and increase dependability and thus increase overall cost for public heath and social service of a country. Therefore, scientifically diagnostics of the poor postural condition is receiving more and more attention from health, medical and sports academy in the past decades since it can detect an incipient fault at an early stage. Though no authenticated statistics for Indian elderly population can be found, it can be safely presumed that situation is no more different in India as increased urbanization and nuclear family concept which has led to the breakdown of traditional healthcare of elderly as discussed by Fuhrer (2014), Beauchet et al. (2008).

Sports professional can use gait analysis techniques to optimize and increase athletic performance. Analysis results may suggest potential injury; the subject can take preventive action. In injury, gait analysis can aid in selecting best available treatment options (Owusu 2007). De Silva et al. (2008) discusses that movement analysis of sports player, prevents possible sports injury. Silva et. al demonstrates that wearable sensors based analysis can effectively prevent many injuries from overuse or incorrect posture and motion in games (Novatchkov and Baca 2013). Bartlett (2006) discuss the use of Artificial Intelligence in sports such as cricket, soccer, short putters, golf, baseball, running, jumping and weightlifting.

### 4.2 Biometric trait

Biometric systems are based on identifying and classifying individuals using biological traits. Biometric systems generally use fingerprints, palm, iris, face and voice recognition but are not limited to only these traits (Prakash et al. 2016b). The aforementioned biometric systems, have certain weaknesses to counter including unreadable fingerprints, iris scans obscured by eyelashes, eyelids, reflections from cornea or face obstruction due to glasses, different hairstyles, and facial expressions. One issue with these systems is the fact that people are concerned while touching the scanning device or waiting in line for using the biometric person recognition system. People often feel that they can identify a familiar person from afar simply by recognizing the way the person walks. This common experience, combined with recent interest in biometrics, has lead to the development of gait recognition as a form of biometric identification.

Gait recognition is an emerging biometric technology, which involves people being identified purely through the analysis of the way they walk. It has recently attracted interest as a method of human identification because it is non-invasive and does not require the subject's cooperation. Gait recognition could also be used from a distance, making it well-suited to identifying perpetrators at a crime scene. Also, since this approach only analyzes a person's walking style, it can also work on masked subjects.

In today work identification of abnormal activity in crowd play a vital role in avoiding terrorist attacks. Gait can be utilized as one of the biometric traits and can be used in surveillance where a large no of people pass through. Gait recognition is an emerging biometric technology, which involves people being identified purely through the analysis of the way they walk. It has recently attracted interest as a method of human identification because it is non-invasive and does not require the subjects cooperation (Aggarwal and Park 2004; Shirke et al. 2014; Ng et al. 2012; Chai et al. 2011). Presently the methods being used for gait recognition can be broadly divided into two categories model based and model free (Zhang et al. 2011a; Liu et al. 2009; Little and Boyd 1998; Prakash et al. 2015c).

Recently various computational techniques have been proposed to analyze actions, activities and behavior of crowd and individuals (Turaga et al. 2008; Krüger et al. 2007; Hu et al. 2004). Abnormal activities can be monitored to alert the related authority for potential criminal activity using vision based gait analysis (Lee et al. 2014). Gait analysis has a huge potential in identifying the psychology (mental activity analysis) of the individual without contacting the concerned individual (Buxton 2003; Mannini and Sabatini 2010; Janssen et al. 2008; Neverova et al. 2015).

### 4.3 Artificial gait

The desire to improve the quality of life and reliability of rehabilitation drives new research and development activities in several countries. Researchers are evaluating the causes and consequences of various faults in postural deformities and walking gait conditions. Gait analysis can supply useful information about kinematics and kinetics of human walking to be used in the design and manufacturing of humanoid robots. Now, with the new techniques, clinicians can exploit instrumental gait analysis as their regular clinical practice to assess a patient's status, healing, and recovery for complex musculoskeletal and neurological disorders. Treadmills based rehabilitation systems are used by many hospitals for walking on a level surface or climbing stairs. Lokomat developed by Jezernik et al. (2001) has four degrees of freedom (DoF). HapticWalker developed by Schmidt et al., Stair Master, GaitMaster5 Yano et al. (2009) are some of the examples of robotic rehabilitation systems. The walking speed and weight support can be adjusted automatically as per the severity of the disease in case of robotic rehabilitation systems. Gait studies have contributed significantly to the design of artificial limbs (prostheses and orthosis) for amputees and inspired artificial locomotor controllers used in Exoskeletons and robotics. It can be used to evaluate orthosis and prosthesis alignment to the lower limbs as discussed in Sigal and Black (2006). Juang (2000) propose a robotic gait synthesis model based on kinematics using the fuzzy neural network. Kim and Lee (2007) explore Hybrid genetic algorithm and neural network for joint angles prediction based on accelerator data.

Gait analysis is important in normal gait behavior of humanoids. Numerous artificial intelligence based algorithms is available for the same (Baker 2006; Zhang et al. 2013; Sigal et al. 2010; Zhao et al. 2012). Popovic and Popovic (2006) proposed a design of control for a neural prosthesis for walking using artificial neural networks. Heinen and Osório (2006) the authors proposed humanoid gait optimization approach that automatically creates and controls stable gaits for legged robots into a physically based simulation environment. Wawrzyński (2012) explores reinforcement learning with experience for humanoid gait optimization.

### 4.4 Control based applications

Computational techniques and gait parameters can be used to control events in the entertainment industry through human-computer interfaces (Liu et al. 2007; Ke et al. 2013). Animation industry also uses gait analysis concept in pose parameters to make it more realistic (Savva et al. 2012). Based on mood detection from gait analysis, one can control room environment. Nguyen et al. (2005) propose a three dimension system for mixed reality, and it can be used in the entertainment industry to create 3D human avatars. In Liu et al. (2007) proposed an advance mixed reality human interaction approach for better learning and playing experience for children at Singapore Science Center. These approaches can play a major role in live interaction based applications such as virtual reality and video games.

The industry has much potential to utilize gait analysis in vehicle production, crash biomechanics and pedestrian detection and to design a comfortable place to work in, using ergonomics techniques. Gait analysis is used in automotive industry for the proper placement of handles on doors in cars for better customer sanctification. The work on designing for ergonomics, proposed by Webber et al. (2015) has been followed by many researchers and the industry in recent years. In Mavrikios et al. (2006), the authors used virtual reality and simulation models to improve customer satisfaction on ergonomics in automotive industry. Untaroiu et al. (2009) proposed vehicle-to-pedestrian crash (VPC) model, for analysis of pre-impact pedestrian posture using various optimization techniques

### 4.5 Other applications

There are numerous other possible applications of gait analysis based on human activity individually and in the group as well. Abnormal activity in a crowd or at home can play a vital role. Recently researchers also explored harvesting energy during human movement (Lan et al. 2015; Multon et al. 2009). Riemer and Shapiro (2011) analyze human gait cycle using EMG, Qualysis Tracking Markers (QTM), WinDaq, insole pressure sensors and V3D to provide the basic understanding of human locomotion to design a mechanism to harvest energy from heel strike. The field of gait is still not fully explored to its full potential.

## 5 Machine learning techniques

The objective of machine learning techniques is to design algorithms that learn either from experience in the form of the labeled data or automatically discover useful patterns from given data-points. Approaches such as Statistical and Machine Learning techniques has been used for gait data representation and classification (Lai et al. 2009b). Statistical techniques can be used in gait models, the study of effects of various independent variables on dependent variables. It can be used for gait kinetic as discussed in Takahashi et al. (2004), Jones and Walker (2006). Multivariate statistical techniques such as Principle component analysis (PCA) and Linear Decrements Analysis (LDA) can be used to represent gait data for find analysis such as linear relationship (Phinyomark et al. 2014) and surveillance (Boulgouris and Chi 2007; Gaba and Ahuja 2014). These techniques are known as data reduction techniques. But when the nature of the problem is nonlinear or complex, they are not a good choice.

Machine learning techniques can be further subdivided into Supervised (classification based), Unsupervised (clustering based), Reinforcement, Rule-based, Evolutionary (Genetic Algorithm, Particle Swarm Optimization), Probabilistic and Hybrid approaches. Table 4 lists the use of Machine Learning techniques highlighting potential applications.

Machine Learning techniques such as supervised (Neural Network, K-Nearest Neighbor (k-NN), Supporting Vector Machine (SVM), Ensembles (Bagging, Boosting, Random Forest), etc); clustering based (Self-Organizing Map, k means, Fuzzy c means, hierarchical), reinforcing learning, fuzzy logic and Evolutionary approaches are used for gait analysis by Wright and Jordanov (2014) as shown in Table 4. This table highlights machine learning techniques with potential gait application.

### 5.1 Supervised learning

Supervised Learning is considered as a task driven approach where we have input and desired output. A mathematical model is created to map the inputs to the desired outputs. Unseen data should be assigned a class as accurately as possible based on this model. The main objective is to minimize the risk or error. In gait analysis, the data has to be labeled by healthcare professionals. Neural Networks, Radial Basis Function (RBF), Ensembles(Baggiing,Boosting,Random Forest), Decision Tree, K-Nearest Neighbor (k-NN), Support Vector Machine (SVM) etc are included in Supervised Learning.

Neural network is an attempt to computationally replicate the working of biological neural networks. The earliest of the research on mathematically modeling the neurons was done by Warren Mculloch and Walter Pitts in 1943 to formulate artificial neurons. Since then various more sophisticated models of the artificial neurons have been proposed by researchers. The neural network proceeds until it reaches to a certain minimum error or predefined epochs. Neural Network is most widely used for Normal Gait Analysis, Robotic Rehabilization, Sports Monitoring and Tactics, Geriatric Care Surveillance, Activity Recognition as discussed by Chau (2001), Choi et al. (2014), Prentice et al. (2001), Popovic and Popovic (2006), Schöllhorn et al. (2008), Novatchkov and Baca (2013), Begg and Kamruzzaman (2005), Nukala et al. (2015), Janssen et al. (2008), Bartlett (2006). A learning model is developed using the existing data through training and then to validate the same, testing is carried out with either the unknown or known data. For validation the K-fold validation, leave one out etc approaches are used.

Radial basis function (RBF) is know to be the simplest variant of neural network. Joshi et al. (2010) use the spatially localized basis function in feature space for disorder detection. Naive Bayes is a probabilistic approach used in case of availability of prior knowledge and is thus considered as a supervised learning approach. It assumes the Gaussian distribution of values for each class. From a given set of training data, it learns the conditional probability of each feature $x_i \in$ X having class name c $\in$ class label set C (Zhao et al. 2012) use naive Bayes for prosthesis intention detection. Ensembles are used for clinical analysis and prediction model.

Support Vector Machine (SVM) is based on the concept of optimally separating hyper-planes and part of supervised learning (Suykens and Vandewalle 1999). It is a non-probabilistic method that projects the input space onto a high-dimensional feature space non-linearly. The SVM is a robust classifier that essentially uses a kernel function to define

**Table 4** Machine learning techniques highlighting potential gait application

| Technique | Learning | Potential application | Reference |
|---|---|---|---|
| RBF | Supervised | Disorder Detection | Joshi et al. (2010) |
| Naive Bayes | Supervised | Prosthesis-Intention Detection | Zhao et al. (2012) |
| Neural Networks | Supervised | Normal Gait Analysis; Robotic Rehabilitation; Sports Monitoring and Tactics; Geriatric Care Surveillance; Activity Recognition | Prentice et al. (2001), Popovic and Popovic (2006), Schöllhorn et al. (2008), Novatchkov and Baca (2013), Begg and Kamruzzaman (2005), Nukala et al. (2015), Janssen et al. (2008), Bartlett (2006), Neverova et al. (2015) |
| Ensembles (Bagging, Boosting, Random forest) | Supervised | Clinical Gait Analysis | Joshi et al. (2010) |
| Decision trees | Supervised | Disorder Detection; Prediction-Model | Song et al. (2013) |
| K-Nearest Neighbor | Supervised | Surveillance | Choi et al. (2014) |
| Support Vector Machine (SVM) | Supervised | Normal/abnormal gait pathology; Gender and Age-Related Differences; Geriatric Care; Normal Gait Analysis; Clinical Gait Analysis | Wu and Wu (2015), Lai et al. (2009c), Levinger et al. (2009), Zhang et al. (2014), Lan et al. (2015), Zheng et al. (2009), Fukuchi et al. (2011), Begg and Kamruzzaman (2005), Nukala et al. (2015), Phinyomark et al. (2014) |
| Self-Organizing map (SOM) | Unsupervised | Clinical Gait Analysis | Cimolin and Galli (2014) |
| K-means Clustering | Unsupervised | Clustering of Disorders | Van Rooden et al. (2010) |
| Hierarchical cluster analysis | Unsupervised | Clustering of Disorders | Toro et al. (2007) |
| Deep Learning | Semi-Supervised | Human Pose Estimation; Human and group Activity | Zeng et al. (2014), Deng et al. (2015) |
| Markov Decision Process | Reinforcement Learning | Humanoid Gait Optimization; Gait Training | Wawrzyński (2012), Hasson et al. (2015) |
| Fuzzy Logic | Rule Based | Inexact Gait Classes; Muscle activity pattern model; Phase identification; Prosthetic control | Skelly and Chizeck (2001), Yu et al. (2010), Alaqtash et al. (2011), Prakash et al. (2016a) |
| Genetic Algo | Evolutionary | Gait Feature Selection; Heel-toe running model; Humanoid Gait Optimization; Surveillance | Heinen and Osório (2006), Tafazzoli et al. (2014) |
| PSO | Evolutionary | Optimal Classifier Selection; Markerless Motion Capture | Yeguas-Bolivar et al. (2014) |

**Table 4** continued

| Technique | Learning | Potential application | Reference |
|---|---|---|---|
| Nave Bayesian | Probabilistic | Artificial Gait | Zhao et al. (2012) |
| Gaussian process regression | Probabilistic | Kinematics predication model | Yun et al. (2014) |
| HMM | Probabilistic | Human physical activity | Mannini and Sabatini (2010) |
| Fuzzy c-mean | Hybrid | Multiple Gait disorder Detection | Zhang et al. (2011b) |
| Neuro Fuzzy | Hybrid | Artificial Gait | Juang (2000) |
| Fuzzy SVM | Hybrid | Gait monitoring platform | Prasad et al. (2016) |
| Self Organisation ANN | Hybrid | Clinical Gait Analysis | Barton et al. (2007) |

the distribution of data points inside the feature space. Authors such as Begg and Kamruzzaman (2005), Fukuchi et al. (2011), Nukala et al. (2015), Phinyomark et al. (2014), Wu and Wu (2015), Lai et al. (2009c), Levinger et al. (2009), Zhang et al. (2014), Lan et al. (2015), Zheng et al. (2009) uses SVM for study of normal and age-related differences, normal and abnormal gait pathology. SVM is a powerful classifier for small to medium dataset.

Supervised learning techniques is a dominant methodology when labeled training data points are available.

### 5.2 Unsupervised learning

In unsupervised learning, no labeled examples are available to train the model. In this learning, agent attempts to find the similarity among the given data points each having a set of attributes and a similarity measure. Based on this similarity measure, each of the data point is grouped together in a cluster. The number of clusters is predefined. The similarity measure can be taken to be Manhattan, Euclidean, Minkowski, cosine distance etc. The objective is to minimize the intra-cluster distance and maximize the inter-cluster distance. K-mean, Fuzzy k-mean, Hierarchical Clustering, Self-Organizing Map (SoM)are some of the examples of clustering techniques. Clustering techniques are most widely used for categorizing and classifying gait data into groups of disorders based on some common features of the disease (Toro et al. 2007; Cimolin and Galli 2014). These techniques help in diagnosing gait abnormalities or classification of everyday physical activities. In O'Malley et al. (1997), explored fuzzy clustering approach on cerebral palsy children based on temporal distance parameters. Xu et al. (2006) explore k mean, SOM and Hierarchical Clustering to differentiate Normal and pathological gait pattern based on stride length and cadence. In Phinyomark et al. (2015) use hierarchical clustering for clustering healthy group from pathological patients.

### 5.3 Reinforcement learning

Reinforcement learning is very similar to human learning without a teacher. It is motivated from behaviorist psychology of human, where an agent learns to take actions based on the experience, so that it can maximize the rewards, which guides the learning algorithm. The major application of reinforcement learning is in humanoid gait optimization as presented by Wawrzyński (2012). Reinforcement learning paradigm optimizes humanoid step-size using actor-critic experience learning. Hasson et al. (2015) also use reinforcement learning for gait training with directional error feedback rehabilitation. The agent on the treadmill learns gait patterns using reinforcement learning and this experience can be extended to walking over ground.

### 5.4 Rule based learning

Fuzzy logic is best suited for representation of information extracted from inherently imprecise data. The fuzzy logic approach is considered to be a rule-based approach. Fuzzy logic handles imprecision, vagueness, and insufficient knowledge. Fuzzy logic can work in this scenario with reasoning algorithms to simulate human reasoning and judgment making capability in machines. These procedures let researchers build intelligent systems in the areas where data cannot be represented in binary form. Fuzzy logic lets intelligent systems perform optimally with uncertain or ambiguous data and knowledge. Gait phase identification activities are often vague or based on intuition, as one can't clearly differentiate all phases. Skelly and Chizeck (2001) explore fuzzy logic for the prosthetic controller using electrically stimulated locomotion for paraplegic subjects. Prakash et al. (2016a) explored Fuzzy Inference System (FIS) to segment gait phases based on passive marker optical system using knee, hip, time and stage variables. Kyoungchul implemented fuzzy based approach to detect gait phases from foot pressure patterns. The outcome highly depends on the selection of optimal membership value and function, manipulation of linguistic operators and rules.

### 5.5 Evolutionary learning

Evolutionary algorithms [Genetic Algorithm (GA), Particle Swarm Optimization(PSO), etc.] can play an important role in optimization based problems. The concept of these algorithms is that they are motivated from biological evolution, such as selection, mutations, crossover, etc. A fitness function is evaluated and based on the problem it is either minimized or maximized. Optimization can be applied to feature selection in gait; relationship among gait parameters, surveillance, heel-to-running model and optimal classifier selection (Heinen and Osório 2006; Tafazzoli et al. 2014; Yeguas-Bolivar et al. 2014). Slow and uncertain convergence and high computational complexity are some of the limitations of evolutionary approaches.

### 5.6 Probabilistic learning

Probabilistic model is used to express noise and uncertainty using mathematics of probability. Hidden Markov Model (HMM), Gaussian process regression and Bayesian are examples of probabilistic models used in gait analysis for human physical activity recognition, kinematics predication model and artificial gait in Mannini and Sabatini (2010), Yun et al. (2014), Zhao et al. (2012) respectively.

### 5.7 Hybrid learning

For better feature recognition, two or more machine learning techniques are combined for pattern recognition. This new technique is known as Hybrid learning. The combination of neural network with rule-based paradigm (Neuro-fuzzy and fuzzy-neuro model) is proposed by Juang (2000) for creating artificial gait. Zhang et al. (2014) combine rule-based and k mean algorithm (fuzzy c-mean) to identify multiple gait disorder detection. Fuzzy with support vector machine (FSVMs) and self organiation ANN were proposed for clinical gait analysis as listed in Table 4. Researchers combined supervised and unsupervised and constructed a semi-supervised paradigm. With the help of limited labeled data, the model is trained for better results. This is useful when the labeled dataset is either expensive or scarce.

Human crafted feature representation limits the machine learning techniques performance. In the past decade, researchers have designed advances form of neural networks known as deep Learning techniques. It constructs feature from raw data and goes with an end to end training. Deep neural nets with a large number of parameters and hyperparameters are very powerful machine learning systems. Convolutional Neural Network (CNN) is a form of deep learning used for classification problems for image, video, Nature Language Processing (NLP) etc. Recently deep learning has been used in monitoring crowd flux, flow and congestion analysis.

Gait analysis has a huge potentiation in identifying the psychology (mental activity analysis) of the individual without contacting the concerned individual (Gowsikhaa et al. 2014; Mannini and Sabatini 2010; Janssen et al. 2008; Neverova et al. 2015). It is not yet fully explored for the gait analysis. Table 5 highlights the field of gait analysis, pointing out

**Table 5** Applications based machine learning techniques

| Author | Application | Machine learning technique | Input gait parameters | Approach | Remarks |
|---|---|---|---|---|---|
| Prentice et al. (2001) | Normal Gait Analysis | NN | Kinematics and EMG | Hybrid | Gait Muscle Modeling |
| Begg and Kamruzzaman (2005) | Normal Gait Analysis | NN—Standard Back propagation; Scaled Conjugate Gradient; and Back-propagation with Bayesian Regularization (BR) | Spatio-temporal, GRF and Joint angular data | Hybrid | 12 young and 12 elderly; Change in gait due to ageing from their respective gait-pattern characteristics |
| Lai et al. (2009c) | Normal Gait Analysis | SVM | GRF and kinematic features | Hybrid | 14 normal & 13 Patellofemoral pain syndrome patients; Automatic recognition of gait pattern |
| Yu et al. (2010) | Normal Gait Analysis | Fuzzy | Kinematic | Hybrid | Prediction Model-Muscle activity pattern from kinematic parameters |
| Song et al. (2013) | Normal Gait Analysis | Probabilistic graphical model, EM algorithm, Decision tree-HMM CRF | Anthropometeric | NA | Prediction Model-From segment length predict kinematic parameters; Correlated static(leg length, etc)-dynamic(actual figure) model |
| Phinyomark et al. (2014) | Normal Gait Analysis | PCA + SVM | Kinematic | Vision Based | 483 subjects on treadmill; Gender and Age-Related Differences during walking |
| Yun et al. (2014) | Normal Gait Analysis | Gaussian process regression | Anthropometeric | Vision | Prediction Model-12 body parameters to gait kinematic; 113 healthy subjects (50 males and 63 females |
| Prakash et al. (2016a) | Normal Gait Analysis | Fuzzy | Kinematic | Vision Based | Fuzzy based gait phase identification |
| Skelly and Chizeck (2001) | Clinical Gait Analysis | Fuzzy Rules | GRF | Sensor Based | 2 insole FSRs are used for gait event detection. Heel strike and toe off detected in real time |

**Table 5** continued

| Author | Application | Machine learning technique | Input gait parameters | Approach | Remarks |
|---|---|---|---|---|---|
| Van Rooden et al. (2010) | Clinical Gait Analysis | k-Mean and Hierarchical Clustering | Stride length and step frequency/cadence | Vision Based | Diagnosis-Normal or pathological gait pattern |
| Barton et al. (2007) | Clinical Gait Analysis | Self Organization ANN | Kinematic and Kinetics | Hybrid | 129 Gait quality assessment |
| Toro et al. (2007) | Clinical Gait Analysis | Hierarchical Clustering | Kinematics | Vision Based | Clustering CP children from sigittal vision |
| Zheng et al. (2009) | Clinical Gait Analysis | SVM, KStar (KNN) and Random Forest | 5 features-kinematic | Sensor Based | Assessment neuro-degenerative diseases-15 Amyotrophic lateral sclerosis,20 Parkinson's disease, 13 Huntington's disease and 16 normal |
| Levinger et al. (2009) | Clinical Gait Analysis | SVM | Spatiotemporal, GRF | Hybrid | 6 healthy, 11-patient undergo surgery; Monitoring recovery from knee replacement surgery |
| Joshi et al. (2010) | Clinical Gait Analysis | Decision tree, Bagging, BF tree, RF,RBF networks, and Multilayer Perceptron + NN | 11 attributes such as genes, age, Alcohol(ml/day), LDL (mg/dl), BMI (Kg/m2), | Hypertension, smoking, diabetes, History of heard disease, Faily histiry and Other | 487 ADRC dataset-for classification of Alzheimer's and Parkinson's disease |
| Alaqtash et al. (2011) | Clinical Gait Analysis | Fuzzy logic | Limb accelerations and 3D GRFs | Sensor Based | 10 healthy & 4 unhealthy Relapsing remitting multiple sclerosis |
| Zhang et al. (2014) | Clinical Gait Analysis | SVM-linear kernel and RBF kernel | Kinematic and kinetic from Inertial Sensors | Hybrid | 17 young subjects lower extremity muscular fatigue |
| Fukuchi et al. (2011) | Geriatric Care | SVM | Kinematic Variable | Vision Based | 17 young and 17 elder persson treadmill-Age related changes |
| Mazilu et al. (2013) | Geriatric Care | Supervised and unsupervised features + PCA | 3D accelerometers | Sensor Based | DAPHNet datase; Freezing of Gait-detection and Prediction |

**Table 5** continued

| Author | Application | Machine learning technique | Input gait parameters | Approach | Remarks |
|---|---|---|---|---|---|
| Lan et al. (2015) | Geriatric Care | SVM-Multi-class SVM | Images | Vision Based | UCF-Sports dataset; Activity Recog |
| Nukala et al. (2015) | Geriatric Care | NN-BP ANN, SVM | Accelerometers and Gyroscopes data | Sensor Based | 322 subjects, Developed Wireless Gait Analysis Sensor; used for fall detection |
| Wu and Wu (2015) | Geriatric Care | SVM | Kinetic | Sensor Based | 60 persons-identify the small significant difference between lower limbs (left and right) |
| Bartlett (2006) | Sports Monitoring and Tactics | Neural Network and Evolutionary Computing | N/a | N/a | Performance of cricket bowlers, soccer players and shot putters |
| Schöllhorn et al. (2008) | Sports Monitoring and Tactics | Neural Network | Kinematic and Kinetics | Hybrid | Monitoring; Sports Model using NN |
| Novatchkov and Baca 2013 | Sports Monitoring and Tactics | Neural Network | Kinematic and Kinetics | Sensor Based | Monitoring; AI in Weight lifting training |
| Popovic and Popovic (2006) | Robotic Rehabilitation | Neural Network | Sensors | Sensor Based | Design of a control for a neural prosthesis for walking |
| Kim and Lee 2007 | Robotic Rehabilitation | Hybrid Genetic Algorithm + Neural Network CPG | Kinematic from accelerometer | Sensor Based | From sensor data creat joint angles |
| Zhao et al. (2012) | Robotic Rehabilization | Bayesian classification algorithm and clustering algorithm EM Decision tree c4.5 | Kinematic and Kinetics | Hybrid | Movement prediction and judgment of lower limb |
| Juang (2000) | Robotic | Fuzzy Neural Network | Kinematic | Hybrid | Model for robotic gait synthesis |

**Table 5** continued

| Author | Application | Machine learning technique | Input gait parameters | Approach | Remarks |
|---|---|---|---|---|---|
| Heinen and Osório (2006) | Humanoids | GA | Joint angular velocity for each joint | Hybrid | Humanoid Gait Optimization-Automatically create and control stable gaits for legged robots into a physically based simulation environment |
| Wawrzyński (2012) | Humanoids | Reinforcement Learning | Sensor | Sensor Based | Humanoid Gait Optimization-reinforcement learning with experience replay for humanoid gait optimization |
| Chen et al. (2007) | Surveillance | Genetic Fuzzy SVM | Silhouette | Vision Based | 70; Gait Recognition |
| Boulgouris and Chi (2007) | Surveillance | LDA | Silhouette Vision Based | Human Recognition | |
| Rida et al. (2015) | Surveillance | Feature selection mask | Silhouette | Vision Based | CASIA Gait database; Human Recognition |
| Hofmann et al. (2014) | Surveillance | vPCA + LDA + Deep Learning | Silhouette | Vision Based | UCMG and CASIA Database; Human Recognition |
| Tafazzoli et al. (2014) | Surveillance | Genetic Algorithm-KPCA | Silhouette | Vision Based | CASIA Database; Gait Recognition |
| Lan et al. (2015) | Surveillance | Sparse reconstruction based metric learning (SRML) | Silhouette | Vision Based | 20 subject dataset-human and gender recognition |
| Deng et al. (2015) | Surveillance | Deep Neural Network | Images | Vision Based | Collective activity and Nursing Home Dataset; Group activity |
| Neverova et al. (2015) | Surveillance | Neural Network-modified Clockwork RNNs | Human kinematic | Sensor Based | Project Abacus from google-data from mobile phone; Human Recognition |

**Table 5** continued

| Author | Application | Machine learning technique | Input gait parameters | Approach | Remarks |
|---|---|---|---|---|---|
| Janssen et al. (2008) | Activity Recognition | NN-SOM | Kinematic and Kinetics | Hybrid | 22 subject; Recognize emotion(normal,happy, sad, angry) from gait patterns; Effect of music on gait pattern |
| Mannini and Sabatini (2010) | Activity Recognition | Hidden Markov Model | Sensors | Sensor Based | 20 subjects with 20 activity |
| Zeng et al. (2014) | Activity Recognition | Deep Learning-Convolutional NN | Silhouette + Accelerometer | Hybrid | 3 database-Skoda, Actitracker and Opportunity |

the purpose and implementations of different AI techniques with input gait parameter and approach adopted have been added with an additional column of remarks.

## 6 Dataset for gait analysis

In this section, we present a comprehensive survey of free available gait datasets. Large and publicly available datasets are very vital for performance comparison and consistent evaluation. Table 6 summarize some of major publicly available gait datasets since 1997. The datasets are arranged in order of publication year.

Approaches used for gait dataset collection involves vision, sensor, and combination of both. These dataset are different in term of no of subject, subject viewpoint [single and Multiview and no of cameras (1–25)], scene type (indoor and Outdoor), walking style (walking, jumping, running, straight, circular etc), variable walking speed, carrying condition (with and without baggage etc), footwear (with different and without shoes etc.), variable surface condition (incline, treadmill) and clothing and time(in term of months, day time) and night vision. Multiple cameras are mostly synchronized in these datasets. Walking environment considers in datasets include indoor, outdoor, slope based environment, on the treadmill. Discussed Dataset have different applications. The survey illustrate that most datasets was collected are used for gait recognition, others are for the clinical purpose. Now, there is the scope of the new dataset that can be used for recognition human behavior and activity in robust conditions.

For clinical analysis, PhysioBank collected dataset for Neuro-degenerative disease (e.g., Parkinson) in 1997 (Hausdorff et al. 1997). It was collected indoor using 64 patients by using force sensitive resistors. Later in 1999 and 2004 with 15 and 166 subjects they study co-relation of aging and disease such as Parkinson. UCSD dataset from Visual Computing Group of the University of California San Diego was collected for gait recognition using six subject walking patterns in outdoor condition (Little and Boyd 1998). UCSD is considered as the first publically available dataset.

Researchers are also collecting dataset to identify and quantify natural gait pattern and characteristics according to gender and age-group from clinical and biomechanical perspective (Andriacchi and Alexander 2000). But it is not as simple because gait characteristics not only depend on anthropometric parameters but it also varies with cultural and social variations. Several gait studies have been carried out in different countries to get this normal gait characteristic. Spatiotemporal, kinematic and kinetic parameters were considered in study in United States (Kadaba et al. 1990; Moisio et al. 2003; Whittle 2014). In 1998 Bendettie et al. consider kinematic and kinetic data to define normal characteristics of Italian people. Auvinet et al. (2002) consider spatiotemporal parameter in their study for France.

Ryu et al. (2006) analyzed spatiotemporal, kinematic and kinetic characteristics of Korean people. OU-ISIR gait dataset is considered as world's largest gait dataset with 4007 subjects including 2,135 male and 1,872 female with ages ranging from 1 to 94. Indonesian gait dataset suggests the standard spatiotemporal and kinematic parameters for Indonesian. KIST Human gait pattern dataset predicts kinematics parameter for Korean people.

As discusses earlier most of the dataset was collected either for gait or activity recognition considering different environment conditions. Gross and Shi (2001) Dataset was constructed by Carnegie Mellon University, with 25 subjects walking on a treadmill in a room. Six cameras, each placed at 60° was used to capture gait pattern under different environment condition (4 walking pattern, speed, carrying condition and inclined surface).

**Table 6** Survey of available datasets

| Year | Gait dataset | Provided by | No of subjects | No of sequences | Walking environment | Approach | Parameter/s | Device details | Syn* | Application |
|---|---|---|---|---|---|---|---|---|---|---|
| 1997 | Gait Dynamics in Neuro-Degenerative Disease Database | PhysioBank | 64 | – | Indoor | Sensor Based | Ground reaction time, stride interveral | Force-sensitive resistors, VGRF | N/A | Disease and dynamics of the stride time |
| 1998 | UCSD Database | University of California | 6 | 42 | Outdoor | Vision Based | View | Sony Hi8 camera; 1view; 30 pfs, 640 × 480 pixel | N/A | Gait Recognition |
| 1999 | Gait in Aging and Disease Database | PhysioBank | 15 | – | Indoor | Sensor Based | Stride interval | Force-sensitive resistors, VGRF | N/A | Normal gait and Parkinson's disease analysis |
| 2001 | MIT Database | MIT | 24 | 194 | Indoor | Vision Based | View, time | Sony Handycam, 720 × 480, 15 | N/A | Gait Recognition |
| 2001 | Georgia Tech Database | Georgia Tech, Atlanta, GA | 20 | 188 | Outdoor, indoor, magnetic tracker | Vision Based | View, time, distance | – | | Gait Recognition |
| 2001 | CMU Mobo Database | Robotics Institute, Carnegie Mallon University | 25 | 600 | Indoor-treadmill | Vision Based | 4 walking pattern, speed, carrying condition, incline surface | 6 color camera; 60° each | Y | Gait Recognition |

**Table 6** continued

| Year | Gait dataset | Provided by | No of subjects | No of sequences | Walking environment | Approach | Parameter/s | Device details | Syn* | Application |
|---|---|---|---|---|---|---|---|---|---|---|
| 2001 | HID-UMD Database 1 | University of Maryland | 25 | 100 | Outdoor | Vision Based | View | 4 viewpoints | N | Gait Recognition |
| 2001 | HID-UMD Database 2 | University of Maryland | 55 | 220 | Outdoor | Vision Based | View | 2 viewpoints- front, side, top mounted | N | Gait Recognition |
| 2001 | SOTON Small Database | University of Southampton | 12 | – | Indoor | Vision Based | 5 Shoe, 3 cloths, view, 3 speed, 5 bag (without bag) | Green background | | Gait Recognition |
| 2001 | SOTON Large Database | University of Southampton | 115 | 2128 | Indoor, outdoor, treadmill | Vision Based | View | 6 viewpoints | Y | Gait Recognition |
| 2001 | USF Gait Database/ HumanID Gait Challenge | University of South Florida | 122 | 1870 | Outdoor | Vision Based | Surface, show, carrying condition, time, walked around an ellipse in front of cameras. | 2 viewpoints- left & right | | Gait Recognition |
| 2001 | CASIA Database (A) | Institute of Automation Chines Academy of Science | 20 | 240 | Outdoor | Vision Based | | 3 viewpoints | | Gait Recognition |
| 2004 | Gait in Parkinson's Disease. | PhysioBank | 166 | – | Indoor | Sensor Based | Stride interval, demographic information | 16 Force sensitive sensor | N/A | Normal gait and Parkinson's disease analysis; stride-to-stride dynamics |

**Table 6** continued

| Year | Gait dataset | Provided by | No of subjects | No of sequences | Walking environment | Approach | Parameter/s | Device details | Syn* | Application |
|---|---|---|---|---|---|---|---|---|---|---|
| 2005 | CASIA Database (B) | Institute of Automation Chines Academy of Science | 124 | 13640 | Indoor | Vision Based | Clothing, carrying 4 walking condition | 11 viewpoints, | | Gait and gender Recognition |
| 2005 | CASIA Database (C) | Institute of Automation Chines Academy of Science | 153 | 1530 | Outdoor, at night, thermal camera | Vision Based | Speed, carrying condition | | | Gait Recognition |
| 2006 | HumanEva I | Brown University | 4 | 57 | Indoor | Vision Based | Walking, Jogging, Gesturing Combo, Throwing and Catching a ball, Boxing and Combo | 7 viewpoints | Yes | Human motion tracking and pose estimation |
| 2008 | BUAA-IRIP | Beihang University, China | 86 | 3010 | | | Multi view | 7 viewpoints | | Gender classification |
| 2008 | GaitaBase Web-based repository | Royal Children's Hospital, Victoria, Australia | – | – | – | Repository | | | | Web-accessible repository system |
| 2009 | CASIA Database (D) | (NLPR), China | 88 | | Indoor | Hybrid-Vision and Sensor Based | Camera and foot scan | | | Gait Recognition |

**Table 6** continued

| Year | Gait dataset | Provided by | No of subjects | No of sequences | Walking environment | Approach | Parameter/s | Device details | Syn* | Application |
|---|---|---|---|---|---|---|---|---|---|---|
| 2010 | HumanEva II | Brown University | 2 | | Indoor | Vision Based | Combo of Walking, Jogging,Gesturing Combo, Throwing and Catching a ball, Boxing | 4 viewpoints | Yes | Human motion tracking and pose estimation |
| 2010 | TUM-IITKGP Database | Technical University of Munich, IIT kharagpur | 35 | 840 | Indoor | Vision Based | Include dynamic occlusion, walking style, carrying condition | 6 viewpoints | | Gait Recognition |
| 2011 | SOTON Temporal Database | University of Southampton | 25 | – | Indoor | Vision Based | Time (0,1,3,4,5,8,9 and 12 months), View | 12 viewpoints | Y | Effect of time on Gait Recognition |
| 2011 | OU-ISIR Gait Database, Inertial Sensor Dataset | Osaka University | 744 | | Indoor, slop based | Vision Based | Age varation (2–78) | Center IMUZ | N/A | Gait-based human identification |
| 2012 | OU-ISIR Database Treadmill | Osaka University | 122 | 1870 | Indoor | Vision Based | Variable walking speed; clothing | 25 views | | Gait Recognition |
| 2012 | OU-ISIR Database Large Population dataset | Osaka University | 4007 | | | Vision Based | Age variable (1-94) | 2 cameras, 30 pfs; 640 × 480 pixels | | Gender and age-group classification and recognition |

**Table 6** continued

| Year | Gait dataset | Provided by | No of subjects | No of sequences | Walking environment | Approach | Parameter/s | Device details | Syn* | Application |
|---|---|---|---|---|---|---|---|---|---|---|
| 2012 | INDONESIAN GAIT DATABASE | Institut eTeknologi Bandung | 212 | | Indoor | Vision Based | Viewpoint, carrying condition, surface, shoe, time (months) | 1 camera 90 fps, | N/A | Spatio-temporal & Kinematics Parameters |
| 2013 | AVA Multi-View Dataset (AVAMVG) | | 20 | 1200 | Indoor | Vision Based | Multiview | 6 cameras | Yes | Gait Recognition |
| 2013 | KIST Human Gait Pattern Dataset | Korea Institute of Science and Technology | 113 | | Indoor, on treadmill | Vision Based | Multiview | 8 camers | Yes | Predicting human gait pattern kinematics |
| 2014 | OU-ISIR Gait Speed Transition Dataset | Osaka University | 179 | | Indoor, on treadmill | Vision Based | Variable Speed | 1 camera | N/A | Gait Recognition under Speed Transition |

Soton dataset from the University of Southampton has two databases namely small and large database. The small dataset contains 12 subjects walking in the door with a green background. The subject was filmed with walking at a different speed and wearing different clothes and shoes, with or without various bags was constructed in 2001. The Large dataset was the first dataset filmed over more than 100 subjects under three scenario (indoor and outdoor track, treadmill) (Nixon et al. 2001). In 2011 they published temporal dataset containing data of 25 subjects over a large period up to 12 months from 12 views. This database accelerates research for inter-subject recognition and exploring gait recognition technique in different conditions

USF database also known as HumanID Gait challenge data is the widely used gait database. It was collected by University of South Florida in 2001 with 122 subjects walking outdoor in a different walking environment (view, shoes, bag, grass or concrete surface and time up to 6 months) containing 1870 sequences (Sarkar et al. 2005). The characteristic of considering highest no of factors in this database among all existing database at that time makes it suitable for inter-factor analysis on gait recognition.

For biometrics C, security research (2016) from Institute of Automation Chines Academy of Science has four datasets (A, B, C and D). Dataset A filmed 20 subjects from 3 viewpoint (0°, 45° and 90°). It has 19139 images with 2.2 GB. Dataset B created in 2005 contains 124 subjects recorded from 11 views with and without baggage and with and without coat wearing condition. Human silhouettes are extracted and provided to the research community for analysis effect of view angles in gait recognition. Dataset C was collected using an infrared camera in 2005 in an outdoor environment at night. It consists 153 subjects including variation in walking speed (slow, normal, fast and normal waking carrying baggage). This opens the research for gait recognition in a dark environment (at night). Dataset D is a collection of 88 Chines subject's camera image and foot scan. Data was collected by synchronizing camera and Rescan Foot scan in 2009.

Technical University of Munich and IIT Kharagpur collected TUM-IITKGP Dataset, in the year 2010. There were 35 individuals recorded from six viewpoints. Total 840 sequences were filmed during normal different walking style including static and dynamic occlusion with various carrying condition. This database is suitable for gait recognition in occlusion environment.

In 2011, Osaka University collected (Makihara et al. 2012), Gait inertial sensor Dataset (Iwama et al. 2012). It includes 744 subject Spatio-temporal data using center IMUZ walking on slop surface indoor. They consider a larger variation in the age group from 2 to 78. In 2012 collected Treadmill dataset with 25 views (largest so far), walking speed (2-10 km/h) and clothing variations. Due to these variations, it accelerates research for the view, clothing, and speed-invariant gait recognition. In 2012 OU considers 4007 subjects including 2,135 male and 1,872 female with ages ranging from 1 to 94 with two viewpoints, it can use to analysis age-group or gender-based gait classification.

Other important dataset for gait recognition includes UCSD database, MIT database, Georgia Tech database, HID-UMD database 1 and 2 (Collins et al. 2002; Johnson and Bobick 2001; Kale et al. 2002; Cuntoor et al. 2003). To generalize the gait pattern over a larger set of population researches (Mahyuddin et al. 2012; Whittle 2014) collected data.

## 7 Conclusion and future prospective

This paper summarizes the development in gait analysis. Different aspects of gait analysis such as basic taxonomy (gait cycle, normal and abnormal gait) and parameters used have been discussed. A comprehensive review of major survey article published in reputed journals and relevant conferences has been presented. This paper also categorises the available gait approaches into four types. Vision, sensor, others and a hybrid approach are discussed in details. Gait can be used in the analysis (normal gait, clinical, geriatric care and sports), biometric (surveillance and activity recognition), artificial gait (rehabilitation and humanoids), control applications and other applications. Machine Learning techniques such as supervised (Neural network, K-Nearest Neighbor (k-NN), Supporting Vector Machine (SVM), Bagging, Boosting, Random forest, etc); clustering based (Self Organizing map, k mean, hierarchical) reinforcing learning; rule-based fuzzy logic, evolutionary and Hybrid approaches are used for gait analysis. Recently Deep learning based researches are being carried out to explore new applications. Deep learning requires a large dataset to work with. In the end, we discussed some relevant dataset available for gait analysis.

Although a significant exploration has been carried out in gait, still it is far from fully optimized based applications. Promising directions for future research are outlined as follows.

Even the current state of the art in data collection is more accurate but still the system is not able to capture the actual gait pattern of subjects. The existing researcher has revealed that fixed viewpoints and hardware limited its application. There is an urgent need of system where once can analysis the actual gait pattern of a subject in 3 Dimensional space.

Another burning issue in gait analysis is that walking pattern is affected by a large no extrinsic, intrinsic, physical, psychological and pathological factors. Researchers are still not able to find the co-relation between these influencing factors on normal walking.

It is found that the computational techniques are now most widely applied and understood for gait analysis. Gait data is highly heterogeneous, high dimensional, temporal dependent, variable. It is not easy to proceed this data. Beside this, the inability to process natural gait data in their raw form limits conventional computational techniques. Deep learning architectures have a wide scope in identification, classification and detection abnormality in gait data. It overcomes the limitation of the need for engineering by hand (LeCun et al. 2015)

The available dataset, have a larger diversity in term of the walking environment but still insufficient for reliable for various gait analysis. In spite of all, we can't generalize gait pattern of a given person. The number of subjects is still insufficient to generalize a standard gait pattern for a given age-group and given gender. Besides, for biometrics, the number of individual in very limited in comparison to other biometrics such as face and fingerprints. There are not enough samples so that the dataset can be said as biased free on gender and age for example in CASIA Dataset B the ratio of male to female is 3 to 1 while USF dataset is biased toward an age group between twenty to thirty. Currently, there is the scope of a new dataset that can be used for defining normal gait pattern among gender and age groups and can recognition human behavior and activity.

The authors believe that this paper will provide useful references for future research of gait analysis approaches, application, and machine learning techniques.

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