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Human gait analysis based on automatic recognition: A review
Análisis de la marcha humana basada en reconocimiento automático: Una revisión

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Resumen

El análisis de la marcha es una de las áreas de investigación más importantes y desafiantes en entornos clínicos y de computación. La biomecánica de la marcha y el reconocimiento humano de la marcha son dos áreas principales de interés. Las alteraciones en la marcha pueden causar problemas de salud física y mental en las personas, por lo que los diagnósticos y tratamientos derivados del análisis de la marcha óptima son de gran utilidad en el ámbito clínico. Este documento examina los métodos, las aplicaciones y las plataformas de análisis de la marcha, la biomecánica de la marcha, así como los enfoques y conjuntos de datos de reconocimiento de la marcha. Luego, describimos las contribuciones en la cinemática de la marcha hacia adelante, útiles para evaluar marchas como agachado y normal. Además, se describe un marco para el reconocimiento de la marcha antiálgica basado en la actividad humana, utilizando el giroscopio integrado en un teléfono inteligente. Se utilizaron diferentes algoritmos y métricas para realizar el reconocimiento de la marcha, destacando Support Vector Machines, Naive Bayes, k-Nearest Neighbours y Accuracy y F-measure, respectivamente. Finalmente, discutimos los desafíos y las perspectivas futuras en el reconocimiento de la marcha.

Palabras Clave: Análisis de la marcha, biomecánica de la marcha, reconocimiento de la marcha, conjuntos de datos de la marcha.

Abstract

Gait analysis is one of the most important challenging research areas in clinical and computing settings. Gait biomechanics and gait human recognition are two major areas of interest. Alterations in walking can cause physical and mental health problems in people, so diagnoses and treatments derived from optimal gait analysis are very useful in clinical settings. This paper surveys the gait analysis methods, applications and platforms, gait biomechanics, as well as, gait recognition approaches and datasets. Then, we describe contributions in gait forward kinematics, useful to assess gaits such as crouched and normal. Also, a framework for antalgic gait recognition based on human activity, using the gyroscope embedded in a smartphone is described. Different algorithms and metrics were used to perform the gait recognition, highlighting Support Vector Machines, Naive Bayes, k- Nearest Neighbours, and Accuracy and F-measure, respectively. Finally, we discuss the challenges and future perspectives on gait recognition.

Keywords: Gait analysis, gait biomechanics, gait recognition, gait datasets.

1. Introduction to gait analysis

Walking is the biomechanical locomotion action that human beings develop to move autonomously. Gait is the style that each person performs to move the body forward during the alternately limbs cyclic motion. While, gait analysis (GA) is the set of procedures to observe record, analyse and interpret human walking (Stergiou, 2020). This assessment tool traditionally has been based on the observational expertise and knowledge of the specialists. However, recently the instrumentation to measure, process, and analyse the body biomechanics has improved the performance of this approach (Whittle, 2014). Gait analysis has been applied optimally in several areas such as i) robotics, ii) biomechanics, iii) sports, iv) rehabilitation, v) gait disease diagnosis, vi) surveillance, vii) forensics among others (Singh et al., 2018).

Most of the important applications of the gait analysis have been developed in clinical settings, in order to develop disease diagnosis and treatments decision-making. An inability to walk can change a persons life, impacting in its independence and creating significant health problems over both the short and long term. This is why gait analysis and the topics around this

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work are very important. There are two main categories: clinical gait assessment and gait research. Clinical gait assessment has the aim of making detailed diagnoses and planning optimal treatments, whereas gait research focuses on improving the understanding of gait. Gait assessment could be used to determine gait illnesses regarding the medical conditions that involve the locomotor system. A large number of diseases affecting the neuromuscular and musculoskeletal systems and leading to disorders of gait are i) cerebral palsy, ii) Parkinson's disease, iii) osteoarthritis, iv) rheumatoid arthritis, v) stroke, vi) spinal cord injury, vii) myelodysplasia, viii) multiple sclerosis, among others (Levine et al., 2012).

2. Gait analysis methods and platforms

The aim of gait analysis is to identify gait abnormalities by studying the motor performance of the musculoskeletal system during walking. In the functional analysis of the pelvic, hip, knee, and ankle joints, it is evaluated by measuring the angular displacement and the rigidity of its degrees of freedom (DoF) when walking (Rigoldi et al., 2012). There are several methods to perform gait analysis, which can be based only on the expertise of the specialist or on instrumented technological equipment (Kelly, 2020). Commonly, sophisticated systems but with higher costs provide an objective analysis rather than the observational approach. Though, it has often found in clinical settings that the problem can be appropriately managed using simpler techniques.

Tabla 1: Gait acquisition methods and available platforms (Ancillao, 2018; Surer and Kose, 2011; Klöpfer-Krämer et al., 2020; Whittle, 2014).

Methods	Instrumentation	Data	Purpose
Marker-based motion capture	Optoelectronic systems, retro-reflective markers	Marker x, y, z coordinates and their evolution over time	Tracking the subject motion to reconstruct their 3D position.
Markerless motion capture	Camera and RGB-D sensors	Video recordings of gait sequences	Conventional cameras can be utilized without the necessity of using special apparel or hardware.
Inertial measurements	Accelerometer, gyroscope or magnetometer	Inertial time-series	Inertial measurement and analysis.
Floor sensors	Force platforms/pressure matrices	Force and moment vector exchanged with the ground. Coordinates of the centre of pressure	Analysis of ground forces, joint reaction, and muscle force.
Electromiography	Electromyograph	Time-series of the voltage produced by muscle contraction	Analysis of muscle contraction.
Energy consumption	Oxymeter, stethoscope	Time-series of O2 and CO2 levels,	Analysis of energy consumption while walking.
Electrogoniometry	Electrogoniometer	Joint angles time-series	Continuous measurements of the angle of a joint while walking.

The most common observational methods are: the Berg Balance Scale (BBS), dynamic gait index, 10-Meter Walk Test, 6-Min Walk Test, and the Functional Ambulation Categories (FACs). All these methods evaluate the walking ability using different tasks and ranges. Due to the evaluation depends on the specialist experience, the assessments are subjective (Sharif Bidabadi et al., 2019). To overcome these limitations, different methods and devices have been developed and introduced in practice. A GA assessment requires the simultaneous acquisition of different types of biomechanical data, therefore, it is necessary to use different measurement systems which are usually stored within the same database. A summary of the methods commonly used in a GA is presented in Table 1.

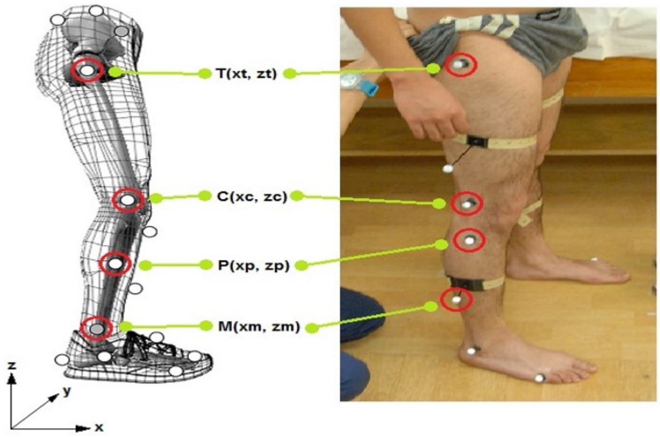

Figura 1: Markers position of marker-based hemiplegic gait analysis system (Correa-Bautista, 2012)

The marker-based motion capture (MoCap) method uses body markers as we can see in Figure 1 is one of the most useful technologies for gait analysis. To this end, the theory of multi-rigid body systems and cameras calibration are required. There are major sources of errors in human movement analysis regarding instrumental errors, environmental variability, soft tissue artifacts and, anatomical landmark misplacement. Also, due to the joint angles are not obtained directly, it is necessary to apply inverse kinematic techniques. Markerless systems, overcome these limitations using conventional cameras without the necessity of using special apparel or hardware. These techniques are classified into model-based and model-free techniques. Model-based approach uses an a priori human body model. While, model-free approaches do not use a human model (Arai and Asmara, 2013). However, the implicitly model variations in pose configuration, body shape, camera viewpoint and appearance are taken into account. The success on the visual GA depends on the number of repetitions and patient motivation (Surer and Kose, 2011).

The digital development of microelectromechanical systems is gaining great interest as a tool for clinical applications. Using inertial measurements for body tracking is a relatively new technology (Mc Ardle et al., 2020). Accelerometers, gyroscopes, and magnetometers have been used to develop gait acquisition systems in both clinical and free-living environments, which are useful for identifying gait abnormalities (Li et al., 2018; Steinmetzer et al., 2020), age-based characterization (Mariani et al., 2010), hemiplegia (Fang et al., 2014). An advantage of this technology is the possibility to perform real-time evaluations. Also, by placing these sensor units to each joint segment of the human body, the orientation of each segment relative to a global frame could be calculated (Sprager and Juric, 2015).

Over the last few years, recent work floor sensors have been applied for medical applications such as the impact of muscle fatigue on gait characteristics, health monitoring, and age-based classification (Alharthi et al., 2021); as well as characterization of gait abnormalities in multiple sclerosis, Parkinsons disease, or fibromyalgia patients (Klöpfer-Krämer et al., 2020). A force platform (or a force plate), integrates devices with either strain gauges or piezoelectric transducers. For gait analysis force platforms are fixed in the ground and they record the force between the ground and the plantar surface of the foot (Ancillao et al., 2018). The disadvantages of using force plates are: the need to be built on a walkway, the number of contact surfaces is limited and a single foot is a measurement during a gait cycle. In the same way, Electromyography (EMG) is a used technique in gait biomechanics to study the muscle of each body segment (Nazmi et al., 2019). Three important applications of surface EMG signals are initiation of muscle activation, force generation by a muscle, and measurement of the fatigue within a muscle. The problem with EMG signals is the semi-quantitative approach and the little measure of the strength of contraction of individual muscles. Also, it may be quite difficult to obtain satisfactory recordings from a walking subject due to the characteristics of the electronic equipment and the electrodes (Kazemi et al., 2017; Schmidt et al., 2020; Rossi et al., 2018).

Another device that has been used for making continuous measurements joint angles is an electrogoniometer. The output function is usually plotted as a chart of joint angle against time or percentage of the gait cycle. (Di Nardo et al., 2020). Oxygen consumption (Darter et al., 2013) and heart rate monitoring (Cheung and Vhaduri, 2020) also have been methods to assess a patient during walking. Recently, several technological platforms for GA have been developed. For example, the GAITRite System is a truly portable single-layer pressure-sensitive walkway measuring temporal and spatial parameters and providing easy identification of gait anomalies (Khan et al., 2019). BTS GAITLAB is a system with 8 motion capture cameras, 6 force plates which performs clinical motion and gait analysis used to evaluate ground reaction forces during gait in people with unilateral transtibial amputation, a series of cases (Cardona et al., 2021). Another system is Wearable FSR sensor used to measure the pressure distribution and changes on an insole, can collect the force applied positions and pressure changes information while walking, running, jumping (Xiao and Menon, 2014). Also, the gait analysis tekscan includes force plates, motion capture, and EMG systems. for gait research and evaluations through objective and quantifiable data and it has been used to validate a SmartInsoles Cyber-Physical System (CPS) to measure gait parameters of multiple users in a restriction-free environment (Arafsha et al., 2018).

3. Gait Biomechanics

Biomechanics is a scientific discipline based on methods of mechanical engineering to analyze biological systems performance. Since gait is considered a mechanical process that is performed by the human body, it could be studied in this way (Levine et al., 2012). While gait kinematics studies the velocities, accelerations, and displacements during the gait, gait kinetics focuses on the forces and torques that generate the body movements. Some areas of biomechanics inquiry that have been addressed are: developmental, exercise, rehabilitative, occupational and forensic (Stergiou, 2020). Kinetics and kinematics analysis of the hip, knee, and ankle joints has been used to assess the effects of a hip arthroplasty (Beaulieu et al., 2010), chronic stroke evolution (Ogihara et al., 2020), Achilles tendinopathy (Munteanu and Barton, 2010), rheumatoid arthritis (RA) (Weiss et al., 2008), inversion sprains (Chinn et al., 2014), and strategies on the gait of patients with Parkinsons disease (Xu et al., 2021).

To better carry out GA, the terminology used must be understandable. In Figure 2, the stages and phases of the gait cycle using as a reference the right lower limb (green) are presented. To this end, we adapt the 2392 OpenSim musculoskeletal model. As we can see, the cycle consists of two phases: stance and swing, and four and three stages, respectively. The main parameters used in clinical settings for GA are: stride velocity, step length, stride length, cadence, cycle time, speed, step width, step angle, step time, swing time, stance time, ground reaction forces, joint angles, muscle force, and momentum (Muro-De-La-Herran et al., 2014).

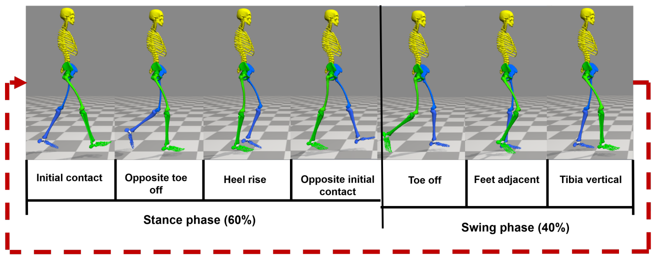

Figura 2: Saggital of positions of the lower limbs during the human gait cycle.

In the same sense, today in a GA test it is important to consider demographic parameters such as age, duration of the disease, sex, place of residence, place of birth, employment (Arellano-González et al., 2021). The environmental parameters such as lighting, temperature, noise, humidity, among others, must be considered. To understand pathological gaits, it is necessary to compare these with the normal gait parameters. Frequently, a global GA test is presented based on Kinematic, spatiotemporal and kinetic gait parameters, in the three anatomical planes (sagittal, coronal and transverse).

3.1. *Gait forward kinematics and visualization*

Human gait biomechanical research is a current essential area, in which individuals of different ages and conditions are examined to determine gait diseases from abnormalities regarding the gait normal parameters. Researchers in this area focus on building body models which explain the functioning of the body system and provide solutions to improve the methods for GA. Acquiring and analysing kinematic and kinetic data of the body-segments and joints of interest have been a common procedure (Surer and Kose, 2011). In previous work we presented a method for gait forward kinematics of position to model the lower limbs during walking. Quaternions algebra was used as a mathematical tool to solve the inverse kinematics of the 8 DoF proposed chain (Figure 3a) and comparative analysis with classical methods was carried out.

Using the same approach, a determination of the difference in the cartesian space performance between normal and crouched gaits was performed. To this end, statistical metrics such as area, RMS level and centroid were used. Also, a visualization of the three anatomical planes for the workspace performance was presented (Gonzalez-Islas et al., 2020). The gait data obtained evaluating the kinematic parameters are big and multidimensional. So, the manual data analysis carried out implies a high temporary, economic, and high specialty cost. Which can lead to errors and a subjective evaluation done by specialist. Therefore, an automatic analysis based on machine learning is possible.

Visual gait analysis is the most common human-based way to assess gait performance. The use of video recording or virtual visualizations also makes it possible to observe gait abnormalities. Showing the subject a video recording of their gait is very useful although, it is not considered biofeedback, since it is not performed in real-time. However, with the advantage of technology adds it could be possible. When a therapist is working with a subject to assess and correct a gait abnormality, the subject may gain clear feedback about their performance.

For the human being, in addition to the basic senses, there are other sensory mechanisms such as the kinesthetic, which is controlled by the receptors in the muscles, tendons, and joints. Therefore, the way that we think and process emotions is reflected in human behavior and gait. An internal biological and/or biomechanical stimulus depends on the mental state of the individual at that moment. The way in which it is interpreted determines the choices that are made at a cognitive and emotional level to express a motor response. Emotional states are interrelated with the human gait, the current understanding of human motion linking emotions and gait would benefit from further work in contributing to a more in-depth understanding (Kelly, 2020).

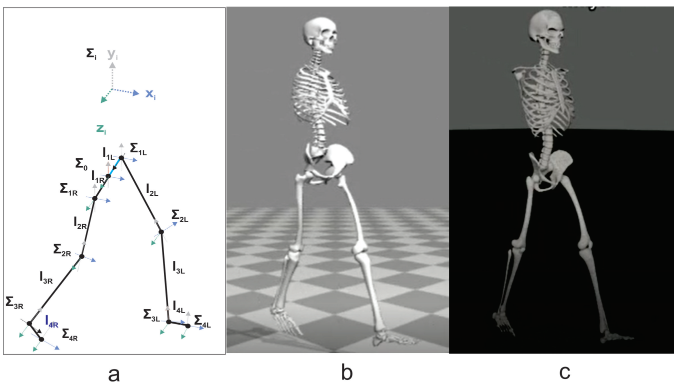

Figura 3: a) 8 DoF Kinematic open chain to model the gait cycle, b) 2392 Opensim Musculoskeletal model (Seth et al., 2018) and c) Maya Human skeletal model.

4. Gait recognition

During the last decades, gait analysis has been studied an improved by the computer community. Gait recognition is a computational approach based on gait pattern analysis, which is used for examining and comparing different subjects. In areas such as person identification (Figure 4), gender classification, surveillance, forensics, and diagnosis of diseases GR has been applied (Singh et al., 2018). In clinical settings, Parkinson's disease detection (Saad et al., 2017), rheumatoid arthritis (RA) evaluation (Raziff et al., 2016), cerebral palsy detection (Taborri et al., 2015), as well as, chiropractic and orthopedic (Hnatiuc et al., 2021) diagnosis, and prediction of lower-limb fracture rehabilitation (Pla et al., 2017). The variations in gait parameters between the subjects allow to differentiate them or determine some abnormalities regarding a normal gait pattern.

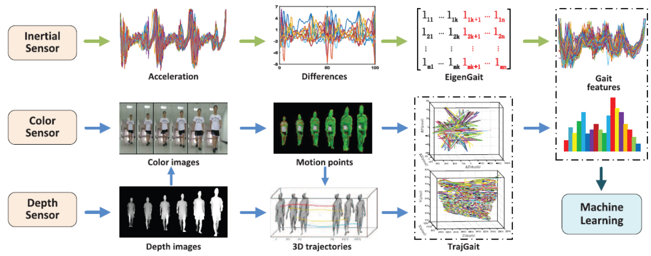

Figura 4: Flowchart of gait recognition system by integrating inertial and RGBD sensors (Zou et al., 2017).

4.1. *Gait recognition framework*

The fundamental framework of a gait recognition system consists of two stages, which are training and testing as shown in Figure 5 (Wan et al., 2018).

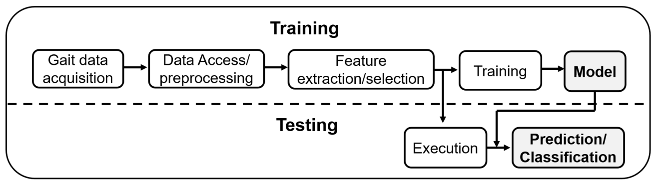

Figura 5: Machine learning framework for gait recognition.

4.1.1. *Data acquisition*

The first module of the training phase is gait data acquisition, which is important for collecting human gait data according the experimental design and the accuracy of the system. Depending on the gait parameters, there are several acquisition platforms such as i) Wearable sensor (Figure 7), ii) floor sensors iii) cameras and iv) Myolectric sensors (Sahu et al., 2020).

4.1.2. *Access and preprocessing*

The first step in any machine learning project is data access and visualization, which is useful for understanding the properties of the data. Common ways are visualizations, signal processing, and clustering techniques. Generally, gait raw data are: noisy, multidimensional, multivariable, missing, and outliers. Therefore, preprocessing tasks including data cleaning, data integration, data reduction, and data transformation are required (Mathworks, 2018).

4.1.3. *Feature extraction\selection*

One of the most important parts of any gait recognition system is feature extraction. It turns gait raw data that could be understandable without redundancy for machine learning algorithms (Sahu et al., 2020). Different data acquisition methods require different feature extraction techniques. In Table 2 a summary of this stage is presented.

Tabla 2: Summary of feature representation methods for gait recognition (Wan et al., 2018; Singh et al., 2018).

Model-based	Model-free	Accelerometer and Gyroscope	Floor sensors
Stride length/cadence	Direct Silhouette	Mean/Standard deviation	Heel strike
Step length	Motion-Energy Image/Motion-History	DTW distance	Foot strike
Gait periods	Gait Energy Image/Gait History Image.	Range	Area
Distance b/w joints	Frame Difference Energy Image	Energy	Length
Stance width	Active Energy Image	Spectral entropy	Mean and standard deviation
Joint rotation patterns	Distance-based features	Median Frequency	Axis relationship
Motion trajectories	Centroid-based features	Correlation	Amplitude spectrums
Orientation limbs	Gait Flow Image	Mutual information	End point and its amplitude

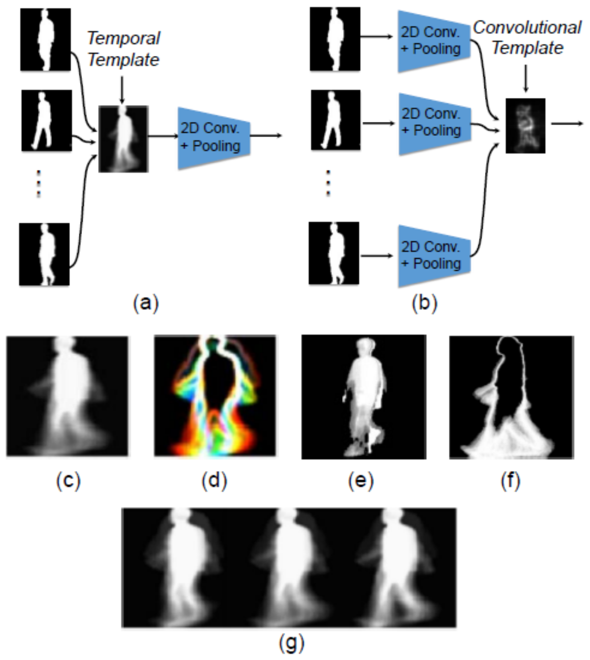

Figura 6: Overview of temporal representations of silhouettes gait sequences (Sepas-Moghaddam and Etemad, 2022).

In vision-based gait recognition, features are extracted based on model-based and model-free representations. Model-based feature representation aims to model the human body, and features are extracted from this model. It typically includes distances and angles of some points on human bodies. Model-based methods are view-invariant, scale-invariant and are not affected by background cluttering and noise. There are two approaches in this sense. First, structurally-based, which estimates the geometrical and structural properties of individual subjects. Second, the 3D model-based aims to identify the discriminative features that differentiate people according to their gait (Singh et al., 2018). In model-free approaches, no prior geometric model of the human body is formed, but they process the whole motion or shape of human silhouettes. Temporal representation based on templates is an approach used to represent the temporal information in of silhouettes gait sequences as we can see in Figure 6 (Sepas-Moghaddam and Etemad, 2022). It is independent of video quality and lower computational cost. However, it depends on viewpoints and scale (Wang et al., 2010).

Wearables are recently considered one of the most suitable technologies for healthcare, security, sports, and fitness applications. In gait analysis, accelerometers, gyroscopes, inertial measurement units (IMUs), and force sensors have been used to measure gait characteristics (Saboor et al., 2020). Two feature extraction methods for this are gait-cycle-based and frame-based methods. In some gait recognition systems, multiple accelerometers are attached simultaneously to human bodies to get multiple gait signals. To this end, signals sources need to be fused (Dehzangi et al., 2017). The simplest way for representing floor-sensor data is body mass. In this way, the body mass information can be used for identifying a person. However, since many individuals may have the same body mass, the recognition rate may below. The floor sensor system captures spatiotemporal samples due to varying ground reaction force (GRF) in multiples of up to 4 uninterrupted steps on a continuous area (Alharthi et al., 2021).

To avoid many features, which were extracted in the last stage, feature selection is a required process. Using too many features leads to overfitting and more computational resources during the training stage. Feature selection (or dimensionality reduction) is the process of deficiently selecting the features that are more relevant, preserving the essential raw data information and removing redundant features. There are common feature selection approaches such as stepwise regression, sequential feature selection, and regularization, Principal Component Analysis (PCA), Genetic Algorithms, Support Vector Machines (SVM), Particle Swarm Optimization (PSO), Discrete Cosine Transform (DCT), among others (Figueiredo et al., 2018).

Tabla 3: Summary of the classification algorithms and its benefits and disadvantages (Singh et al., 2018; Pogorelc et al., 2012).

Algorithms	Benefits	Disadvantages
K-Nearest Neighbors (k-NN)	If training data is large, it is simple and efficient.	Lower accuracy. Does not work well with high dimensions.
Naive Bayes (NB)	Simple and easy to implement. Fast, since it requires less training data. It makes probabilistic predictions	Unable to make predictions
Support Vector Machines (SVM)	High accuracy. Handles high dimensional data well.	Not suitable for large datasets
Deep Conventional Neural Networks (DCNN)	High accuracy. Popular for classification, compression and recognition.	It needs more training data. High computational cost
Decision Trees (DT)	Good generalizing	Prone to overfitting
Random Forest (RF)	Highest accuracy. It can also handle big data.	Low prediction accuracy

4.1.4. *Classification*

The last stage of the gait recognition framework is classification, which is an iterative process to develop a model and involves these steps: i) Select the training and validation data, ii) Select a classification algorithm, and iii) Train and evaluate classification models. Before training classifiers, we need to divide the data into training and validation sets, in which randomly 80 % and 20 % of the data, respectively are assigned (Sugomori, 2016). Then, iterative training and evaluation of models is performed. It is possible to follow the brute force approach and run all the algorithms, or start with the algorithms with better performance for gait recognition. Classification is divided into two categories: supervised and unsupervised. In table 3, we present a summary of the most common methods used for this task.

k-NN is the most used classifier in gait recognition. There are various ways to evaluate the performance of a gait recognition model. The most common way is the use of the generalized metrics for n experiments, which are presented as follows (Gonzalez-Islas et al., 2021).

- Accuracy (Acc)

$$\overline{Acc} = \frac{1}{n}\sum_{i=1}^{n}\frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} * 100 \quad (1)$$

- F-measure (F)

$$\overline{F} = \frac{1}{n}\sum_{i=1}^{n}\frac{2P_iR_i}{P_i + R_i} * 100 \quad (2)$$

- Sensitivity o Recall (R)

$$\overline{R} = \frac{1}{n}\sum_{i=1}^{n}\frac{TP_i}{TP_i + FN_i} * 100 \quad (3)$$

- Specificity (SP)

$$\overline{SP} = \frac{1}{n}\sum_{i=1}^{n}\frac{TN_i}{TN_i + FP_i} * 100 \quad (4)$$

- Precision (P)

$$\overline{P} = \frac{1}{n}\sum_{i=1}^{n}\frac{TP_i}{TP_i + FP_i} * 100 \quad (5)$$

Accuracy is used when the true positives (TP) and true negatives (TN) are more important, while F-measure (F) is useful when the false negatives (FN) and false positives (FP) are crucial. Where, TP are the positive correctly classified instances, TN are the negative correctly classified instances, FP are the outcomes misclassified as the positive class, and FN are instances misclassified as the negative class. Also, other metrics such as: Sensitivity (R), Specificity (SP), Precision (P) (Jun et al., 2020), are used to evaluate the performance.

4.2. Gait datasets

In order to evaluate gait recognition systems, different datasets using different data acquisition platforms have been collected. in Table 4 a summary of the gait datasets, with their DAQ platforms, as well as description is presented.

As you can see in Table 4 there are several gait datasets with recognition purposes. CASIA Gait Database also has other two datasets A and B: The first includes 124 subjects and the gait data were captured from 11 views. While the second one contains 153 subjects and takes into account four walking conditions: normal walking, slow walking, fast walking, and normal walking with a bag (Zheng et al., 2011). Similarly, The ASIS Gait database, contains other data sets such as (2015) Marker-name labelled raw data of five gait cycles (right heel contact to next right heel contact) obtained from 214 participants and (2019) NoCap data of ten gait cycles (5 gait cycles started from right heel contact and 5 gait cycles started from left heel contact) obtained from 300 participants (Takayanagi et al., 2019).

Tabla 4: Available datasets for gait recognition. Where DAQ is data acquisition

Dataset	DAQ platform	Description
OUISIR Inertial Sensor-based Gait Database (Ngo et al., 2014)	Three inertial measurement units (accelerometer and gyroscope) and a smartphone around the waist of a subject,	744 subjects (389 males and 355 females) with ages ranging from 2 to 78 years.
OU-ISIR Gait Database (Takemura et al., 2018)	Camera	10,307 subjects (5,114 males and 5,193 females with various ages, ranging from 2 to 87 years) from 14 view angles, ranging 0-90, 180-270.
MAREA (Khandelwal and Wickström, 2017)	Accelerometers on waist, wrist and both ankles	(20 healthy subjects) that consists of walking and running in indoor and outdoor environments.
CASIA Gait Database (Zheng et al., 2011)	Camera system	20 persons.(Dataset A). Each person has 12 image sequences, 4 sequences for each of the three directions.
AIST Gait Database (Takayanagi et al., 2019)	Optical motion system	2013. Marker-name labeled raw data of one gait cycle (right heel contact to next right heel contact) obtained from 139 participants were included.
Gait Dynamics in Neuro-Degenerative Disease Database (Hausdorff et al., 2019).	Force-sensitive resistors, with the output roughly proportional to the force under the foot	Collection of 64 recordings of gait from 15 subjects with Parkinson's disease, 20 with Huntington's disease, 13 with amyotrophic lateral sclerosis, and 16 healthy controls.

Gait in Aging and Disease database includes walking stride intervals time series from 15 subjects: 5 healthy young adults (23 - 29 years old), 5 healthy old adults (71 -77 years old), and 5 older adults (60 - 77 years old) with Parkinson's disease. The stride interval was measured using ultra-thin, force-sensitive resistors placed inside the shoe (Hausdorff et al., 1998). Parkinson's disease (PD) is one of the most common movement disorders. The database Gait in Parkinsons Disease aims the measure of gait of 93 patients with idiopathic PD (mean age: 66.3 years; 63 % men), and 73 healthy controls (mean age: 66.3 years; 55 % men). The database includes the vertical ground reaction force records of subjects as they walked at their usual, self-selected pace for approximately 2 minutes on level ground. Underneath each foot were 8 sensors (Ultraflex Computer Dyno Graphy, Infotronic Inc.) that measure the force (in Newtons) as a function of time. The output of each of these 16 sensors has been digitized and recorded at 100 samples per second, and the records also include two signals that reflect the sum of the 8 sensor outputs for each foot. (Frenkel-Toledo et al., 2005)

On early age, gait is unsteady. However, there is a hypothesis that gait dynamics would continue to develop beyond age three. For this reason, gait cycle duration on a stride-by-stride basis in healthy children (n=50) ages 3 to 14 years old were measured and storaged. A portable foot-switch device inserted inside of shoes was used. (Zakaria et al., 2014). Elder adults also are a very important community, Long Term Movement Monitoring Database contains data of a seventy-one community (mean age = 78.36 4.71 years; range = 65-87 years). Subjects were classified as fallers and non-fallers based on their self-report of previous falls (Goldberger et al., 2000).

Wearable sensors are a widely used technology for GA. (Luo et al., 2020) present a database of human gait performance on irregular and uneven surfaces collected by wearable sensors This database provides data from thirty participants (fifteen males and fifteen females, 23.54.2 years, 169.321.5cm, 70.913.9kg) who wore six IMUs while walking on nine outdoor surfaces with self-selected speed (16.44.2 seconds per trial). Human motion capture is frequently used in GA, (Schreiber and Moissenet, 2019) to describe a multimodal dataset of human gait at different walking speeds on injury-free. The experiment was established for 50 adult participants adults healthy and injury-free for lower and upper limbs in the most recent six months, with no lower and upper extremity surgery in the last two years. Participants were asked to walk on a straight-level walkway at 5 speeds during one unique session. Three-dimensional trajectories of 52 reflective markers spread over the whole body, 3D ground reaction forces and moment, and electromyographic signals were simultaneously recorded. For each participant, a minimum of 3 trials per condition have been made available in the dataset for a total of 1143 trials.

The AVA Multi-View Dataset for Gait Recognition (AVAMVG) contains 200 multi-view videos or 1200 (6 x 200) single view videos. They establish twenty humans (4 females and 16 males), participated in ten recording sessions each. Ten gait sequences were designed before the recording sessions. All actors depict three straight walking sequences, and six curved gait sequences as if they had to round a corner (López-Fernández et al., 2014). Bradford Multi-Modal Gait Database is a Gateway to create a dynamic gait signature. 30 subjects conducting four forms of gait (walk, run, walk to run, and walking with a handbag) were evaluated. Each subject recording included a total of 8 samples of each form gait, and a 3D point cloud (representing the 3D volume of the subject) (Alawar et al., 2016). Finally, TUM-GAID was introduced by (Castro et al., 2019) collects 305 subjects performing two walking trajectories in an indoor environment. Two recording sessions were performed, and the action was captured by a Microsoft Kinect sensor which provides a video stream with a resolution of 640480 pixels and a frame rate of around 30 FPS.

4.3. *Antalgic gait recognition based on human activity*

Antalgic gait is one of the most common abnormal gaits. In a previous work we present a framework for antalgic gait recognition (Gonzalez-Islas et al., 2021), using the embedded gyroscope (a signal for each axis) of a smartphone for data acquisition. The test carried out was 10-meter walk, with a population of 30 subjects, 40 % antalgics, and 60 % non-antalgics. The experimental data acquisition setting and correspondence between the anatomical axis and gyroscope axis are presented in Figure 7.

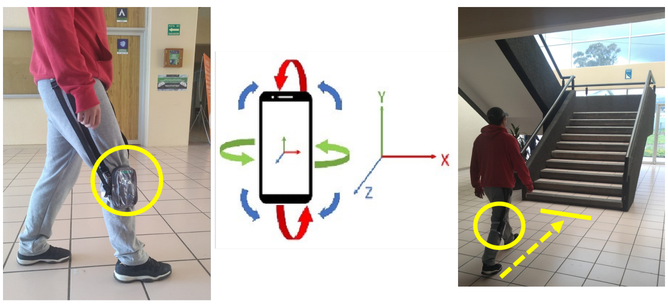

Figura 7: Wearable acquisition setting for antalgic gait recognition, using a embedded gyroscope.

The classification algorithms used were: i) K-Nearest Neighbors (k-NN), ii) Naive Bayes (NB), iii) Support Vector Machines (SVM), iv) Discriminant Analysis (DA), v) Decision Trees (DT), and vi) Classification Ensembles (CE). The performance of the algorithms was evaluated using the metrics: Accuracy (ACC), Sensitivity (R), Specificity (SP), Precision (P), and F-measure (F). The equations presented in section 4.1.4 were used for this purpose. A summary of the metrics performance for each classification method is shown in the Table 5.

Tabla 5: Summary of performance of classification methods for antalgic gait recognition (%) (Gonzalez-Islas et al., 2021).

Algorithm \Metric	**Acc**	**F**	**R**	**SP**	**P**
SVM	98.88	97.77	100.00	100.00	98.66
k-NN	99.44	100.00	99.33	98.33	98.88
NB	96.1	91.66	100.00	100.00	94.82
DA	98.33	99.16	98.33	98.33	98.41
CE	89.44	88.22	91.22	87.22	87.34
DT	89.44	86.66	93.72	89.16	84.12

As it can be seen, SVM and k-NN were the models with better Accuracy performance of 98.88 % and 99.44 %, respectively. The implementation of this framework in a real scenario for diagnosing diseases related to antalgic gait is supported by the obtained results.

4.4. *Gait Recognition challenges*

Currently, although there are significant advances in gait recognition systems, there are still open research topics. The challenge for gait recognition systems is efficiency in real-world applications. Real gait data are large, noisy, multivariable, multidimensional, multi-source origin. Also, conditions such as lighting, viewpoints, walking surface, physical (pregnancy, leg or foot injuries), clothing, footwear, cluttering environments and occlusion in vision-based systems, represent a big challenge in this area. The aforementioned issues result in problems such as gait occlusion, view, and appearance changes.

In addition, data acquisition platforms for collecting biomechanics, demographic and environmental variables during the gait parameters acquisition affects the performance of the systems. Also, to the aforementioned issues, extraction and, selection of the specific gait features as well as the best algorithm for the specific task to achieve high recognition, is a recurring need. Several gait recognition approaches has been developed and the obtained results provide an encouraging outlook, but there are still issues to improve gait recognition. Although there are several gait datasets these have considerable restrictions, which open a new research direction to solve this need (Sepas-Moghaddam and Etemad, 2022).

Many approaches have been developed to improve gait recognition systems. However, there are some opportunity areas in future research such as gait recognition under occlusion scenario, gait-based anomalies detection, robust gait recognition under appearance covariate, adaptive foreground/background object segmentation, optimized features for efficient gait recognition, and fusion of gait features (Singh et al., 2021).

5. Conclusions

This paper has been focused on a general description of gait analysis, gait biomechanics, and gait recognition, as well as some contributions to this area that we have done. Different gait methods, platforms, and datasets have been mentioned. Although, there are several gait approaches with promising results, today real-world applications with high accuracy are still few. Technological advances in electronic and computing systems allow the development of more efficient gait acquisition platforms, feature extraction and selection, as well as classification algorithms.

Gait biomechanics is another open research area, the need to develop mathematical approaches to model the kinematic and kinetic behavior of the limbs during the walk; particularly when the application of diagnostic criteria is relevant, in which not only the gait is significant for the evaluation, but also the cadence or movement speed. Forward kinematics allows the analysis in the workspace and it makes possible the global performance in the three anatomical planes or local analysis for each. While inverse kinematics, in addition to determining the performance of the joints with respect to the range of movement, allows the reduction in the instrumentation to acquire the parameters of the gait.

Assisted physiotherapy and neurorehabilitation platforms for spastic patients (a consequence of a stroke), establish that exergaming techniques in which walking is involved, represent an alternative that encourages the development of the treatment routine with visual and kinesthetic feedback; the forward and inverse kinematics of the gait (position and velocity) strengthen the realism in this type of platform.

Also, future perspectives in gait recognition were discussed. Each of the framework stages such as acquisition, datasets generation, access and preprocessing, feature extraction/selection and classification affects the performance of any recognition system and require to be improved. Support Vector Machines, K-Nearest Neighbors and Naive Bayes, are the most common and efficient algorithms used for this purpose. In clinical settings, gait diseases diagnosis and decision-making has been supported by recent gait recognition systems and there is an increasing acceptance by clinicians of the results of gait analysis.

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